The Informational Value of Corporate Credit Ratings

Mike Densmore, MSc in Management (Finance)

Graduate Program

Submitted in partial fulfillment

of the requirements for the degree of

MSc in Management (Finance)

Faculty of Business, Brock University

St. Catharines, Ontario

Abstract

This thesis examines the quality of credit ratings issued by the three major credit rating agencies - Moody's, Standard and Poor's and Fitch. If credit ratings are informative, then prices of underlying credit instruments such as fixed-income securities and credit default insurance should change to reflect the new credit risk information. Using data on 246 different major fixed income securities issuers and spanning January 2000 to December 2011, we find that credit default swaps (CDS) spreads do not react to changes in credit ratings. Hence credit ratings for all three agencies are not price informative. CDS prices are mostly determined by historical CDS prices while ratings are mostly determined by historical ratings. We find that credit ratings are marginally more sensitive to CDS than CDS are sensitive to ratings.

Acknowledgments

I would like to express my gratitude to my supervisor, Dr. Skander Lazrak, whose knowledge, expertise and experience added significant value to my university experience. I appreciate his patience and vast knowledge in a variety of useful fields. His ideas, guidance and understanding made the completion of this thesis possible. Furthermore, I appreciate his ability to properly motivate me to pursue challenging and new work. My pursuit of a graduate degree was based on guidance from Dr. Lazrak and for that I am grateful. Throughout both degrees Dr. Lazrak has shown an interest in not only my school life, but also my life outside of school. I sincerely appreciate the guidance and wisdom he has provided.

I also thank the members of my committee; Dr. Mohamed Ayadi and Dr. Robert Welch for the assistance and guidance they provided throughout the completion of my thesis. They each contributed very significant ideas and criticisms adding greatly to the value of this thesis. Furthermore, I am very thankful for the support they both provided through internal job opportunities. Without this work I would not have been able to support myself throughout my degree.

I must also thank a few Brock faculty members who have helped in my success at Brock. I am grateful to Valerie Desimone and Karen Phillips, administrative assistants in the Faculty of Business and Economics departments respectively. Their willingness and success in helping me with virtually any problem faced in a timely and efficient manner has greatly contributed to my success. I am grateful for the vast amounts of time they have taken out of their busy days in order to help with employment issues as well as thesis related issues.

Finally I would like to thank my family and close friends whose support, understanding and patience helped me through the entire process. I am especially thankful for their support during times of frustration which frequently arose. Without the continued support of my close friends and family this thesis would not have been completed.

Table of Contents

List of Tables

Chapter I. Introduction

Rating agencies provide markets with information regarding credit worthiness and presumably reduce uncertainty by increasing the information flow between investors and issuers. The 2011 Standard and Poor's Guide to credit rating essentials states that "Credit ratings are opinions about credit risk. Standard & Poor's ratings express the agency's opinion about the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time". Hence agencies decrease the cost of searching, analyzing and monitoring creditworthiness by investors. This should also lower the cost of lending and borrowing between issuers and lenders.(Moody's Special Comment, 2002).

Recent major systemic credit events have occurred without clear warnings from the rating agencies which questions their informational value. For example consider the downfall of Bear Stearns. Prior to filing for bankruptcy there were ample signals showing their deteriorating credit worthiness which rating agencies failed to recognize. Bear Stearns had two highly levered hedge funds which were invested in the subprime mortgage market. In early 2007 when mortgages began to frequently default these funds started to experience large losses. In July 2007 the two funds collapsed. The rating agencies did not act on this information until November 15th 2007 when S&P downgraded Bear Stearns rating from A+ to A. Ratings were not changed again until March 14th 2008, where S&P lowered Bear Stearns rating to BBB. This followed the announcement of an emergency loan from the FED through JP Morgan. These major events were not surprises. Other markets seemed to lead rating agencies in adjustment. From January 2007 to January 2008 Bear Stearns share price dropped from $171.51 to $71.01.

Further examples include; the recent downgrading of major banks,[1] the 1997 Asian financial crisis that spread to Latin America and various other parts of the world and the earlier Savings and Loans failures for investors and banks in assessing credit risk levels of their portfolios and are designed to complement investor's research. According to Standard and Poor, credit rating agencies can be viewed by investors as impartial because they do not directly engage in capital market transactions. However whether they are truly impartial is the subject of current research.

An issue that tends to arise when determining the degree of neutrality of rating agencies is the manner in which they collect income. There are two methods by which agencies receive payment. The first is the issuer pay model where issuers pay raters to initiate and maintain a credit rating. The second is the subscription pay model where investors pay to access the credit ratings. Both models are criticized because they involve conflicts of interest. When the issuers pay for the rating there is an incentive for agencies to provide higher ratings to retain their business. Under the subscription pay model there is a tendency for agencies to cater to the needs of the investor and therefore provide lower ratings. Another drawback of the subscription pay model, assuming that credit ratings were established to improve the flow of information, is that it is likely to increase informational asymmetry since the ratings are released to the party paying for the service as opposed to the public.

The objective of this thesis is to assess the quality of American corporate ratings given by the three most recognized rating agencies (Standard and Poor's, Moody's and Fitch). High quality ratings are forward looking. They impact issue prices. Informative rating changes trigger bond prices to move in accordance. Our empirical analysis examines whether credit rating reclassifications lead or lag changes in prices. Our price measure is the credit default swap (CDS) price linked to

[1] In June 2012 Moody's downgraded 15 global banks by between 1 and 3 grades. Banks such as Citigroup and Goldman Sachs publicly questioned Moody's methodology after being downgraded (Campbell and Moore, 2012).

specific issuers. CDS contracts are insurance against default events. We opt for CDS prices as they relate more to credit and default risk than yields.

Our main result is that credit ratings are not forward looking regardless of the rating agency. Using data spanning the 2002-2011 period and covering 246 different issuers rated by the three major rating agencies, we empirically document that ratings do not influence credit default swap prices after controlling for appropriate factors. This finding supports the hypothesis that rating agencies do not contribute to the informational efficiency of the credit market.

Our contribution to the literature is twofold. First, we use a methodology we deem more appropriate for the test. Vector AutoRegressive (VAR) and Vector Error Correction (VEC) models are more suitable to test the feedback effects and the mutual contributions in the innovations of endogenous series. Second, our analysis encompasses the recent financial crisis and dramatic credit rating changes which provide more power to our tests.

The remainder of this thesis is organized as follows. Chapter II reviews the literature about the quality and the evolution of credit rating. Chapter III describes the methodology used to test for the quality of credit rating. Chapter IV discusses the sample construction and provides descriptive statistics about the issuers included in the current study. Chapter V develops the empirically testable hypotheses and presents the empirical findings. Chapter VI concludes the thesis.

Chapter II. Literature Review

Empirical and analytical studies have been conducted on credit rating changes. Literature on the informational value associated with rating reclassifications employ a variety of statistical methods and obtain mixed results. This thesis focuses on assessing the quality of issuer credit ratings and how quality evolves over time. A review of the literature studying different aspects of credit rating reclassifications follows.

Much of the literature on credit rating changes has adopted some form of event study methodology, whether it be the market model, one factor model, two factor model or some other variation. Past studies have used both the date of the physical rating change and the announcement of change as the event date.

In order to measure the informational value of rating reclassifications most previous studies have looked to bond yields and stocks prices for the anticipation of (or reaction to) a change in credit rating. There are a few that make use of credit default swap (CDS) spreads in measuring this effect (Hull et al. 2004; Norden and Weber 2004). In this paper we examine the lead-lag relationship between CDS spreads and credit rating reclassification. Subsection 2.1 reviews studies which analyze ratings quality using monthly bond yields. Subsection 2.2 presents studies using weekly and daily bond yields. Subsections 2.3 and 2.4 present studies that use equities markets in analyzing ratings quality. Studies in subsections 2.3 and 2.4 examine monthly and daily stock prices, respectively. Subsection 2.5 reviews research studying how ratings quality changes with certain historical events. Lastly, studies analyzing CDS market reaction/anticipation to credit ratings changes is presented.

2.1 Monthly Bond Yield Effects

Katz (1974), Grier and Katz (1976), Weinstein (1977) and Hite and Warga (1997) contribute to the studies on bond market efficiency by examining monthly bond performance following a credit rating reclassification with event-study methods. Katz (1974), Grier and Katz (1976) and Heinke and Steiner (2001) results contradict market efficiency whereas Weinstein (1977), Clauretie et al. (1992) and Hite and Warga (1997) obtain findings in favor of market efficiency.

Katz (1974) examines the behavior of the yield to maturity in the 18 months surrounding the change in rating. His study is limited to Standard and Poor's investment grade electrical utility bonds assuming this industry would provide the most homogeneous operating characteristics so that qualitative differences between firms would be contained in bond yields. Using event study methodology he finds no anticipatory effect before the change and that full price adjustment to a rating reclassification took between 6-10 weeks.

Weinstein (1977) and Grier and Katz (1976) expand upon the dataset used by Katz (1974) by including industrial and public utility bonds with conflicting results. Weinstein concludes in favor of bond market efficiency whereas Grier and Katz (1976) find evidence against bond market efficiency. Grier and Katz (1976) limit their sample to only bonds rated by Standard and Poor's. They also consider only downgrades since very few public utility or industrial bonds were upgraded in the selected time interval. In order to separate the effects of a general change in market credit worthiness they form a control group in the following way; for every bond experiencing a rating change a control bond is found such that it had a similar maturity and yield as well as the same initial rating.[2] When examining both sectors together they find that 80% of the adjustment occurred in the 4 month period containing the month of and the 3 months following a rating change. The combined sample results indicate that, contrary to expectations, intermediate maturities (10-19 years) experience the largest dollar adjustment. Shorter term maturities (0-9yrs) experience the second largest adjustment and long term maturities (20-30yrs) show the least adjustment. They explain this difference between expectations and results by looking at the two different sectors individually. Industrial bonds exhibited much

---

[2] They were also careful to ensure that the control bonds were from the same industry.

higher volatilities in prices than did utility bonds. Utility bonds showed no significant adjustment for short to intermediate term maturities however long term maturities had a 3 month lag in the adjustment.

Weinstein (1977) uses ratings from the three major rating agencies; Moody's, Standard and Poor's and Fitch. He attempts to randomly select bonds that fit the following criteria; non-convertible, trade without undetachable warrants or other securities, have a fixed coupon rate, denominated in US dollars and are issued by a US firm. A potential reason that the results of Weinstein (1977) differ from Grier and Katz (1976) is that he considers both upgrades and downgrades, uses monthly interest adjusted holding period returns (as opposed to prices or yield) and considers a longer event window (24 months). When examining various windows he demonstrates that adjustment takes place between 6 months and 18 months prior to a rating change with no significant adjustment occurring after reclassification.

Hite and Warga (1997) restrict their sample to industrial bonds rerated by Moody's and Standard and Poor's. They use a two year event window and unlike Katz (1974), Grier and Katz (1976) and Weinstein (1977), they compare relative strengths of abnormal returns of re-ratings that cross the investment grade barrier and re-ratings that do not. This is one of the few studies (using bond yields or stock returns) that reports significant abnormal returns associated with upgrades. Hite and Warga (1997) find significant market reaction for upgrades from non-investment grade to investment grade and insignificant results for all other upgrades. They conclude that downgrades to non-investment grade, whether from investment or non-investment grade, result in the strongest adjustment which takes place during the month of the event and 6 months prior to the rating reclassification.

2.2 Weekly/Daily Bond Yield Effects

Clauretie et al. (1992) and Heinke and Steiner (2001) build on previous studies using bond yields by studying the effect of credit watch list additions. The first paper uses weekly bond prices from the Merrill Lynch bond pricing service and credit ratings from Standard and Poor's. Using a market-adjusted returns model they conclude, in line with the majority of previous work using bond prices, that downgrades result in significant negative abnormal bond returns whereas the effects of upgrades are insignificant. The downgrade effect is strongest over the prior two week period and the week of the rating change. Furthermore they determine that additions to credit watch lists do not provide any informational effects. Parallel to Grier and Katz (1976), Clauretie et al. (1992) also find that industrial bonds have more pronounced and significant abnormal returns than utility bonds.

Heinke and Steiner (2001) differ from all other papers because they examine the effects on the German Eurobond market of credit rating changes given by American credit rating agencies (namely Moody's and Standard and Poor's). It is the first study that incorporates daily bond prices in the analysis. Bonds are filtered in a manner similar to Weinstein (1977) in that only plain vanilla bonds are included in the sample. Their results indicate that downgrade announcements and announcements of negative watch lists are associated with significant negative reaction on the event date and up to 4 trading days afterwards. However they note that there is reversion of abnormal returns approximately 3 weeks following the announcement. They find no significant results for upgrades or positive watch list announcements. Given the few restrictions on their sample Heinke and Steiner (2001) are able to make conclusions regarding issuer type[3]. Bank bonds are found to have the smallest reaction while government issued bonds reveal the largest reaction.

There have been several papers devoted to investigating the effect of debt re-ratings in equity markets. Pinches and Singleton (1978), Griffin and Sanvicente (1982) and Vassalou and Xing (2004) analyze credit rating changes using monthly stock returns. Davidson et al. (1987), Followill and Martell (1997), Ederington and Goh (1993), Dichev and Piotroski (2001), and Bannier and Hirsch (2010) provide similar tests using daily stock returns.

[3] Unlike most studies, they did not restrict their sample by issuer type.

2.3 Monthly Stock Returns

Pinches and Singleton (1978) use a dataset including upgrades and downgrades; but study only ratings given by Moody's. Transportation, industrial and public sector bonds are used in their analysis, however only 18 out of the 207 rating changes are from the transportation sector. They calculate abnormal returns using a one-factor market model focusing on the residuals between the 30 months preceding and the 12 months following a rating reclassification. Their main conclusion is that abnormally high (low) stock prices occur prior to bond upgrades (downgrades). They find stock prices to be relatively stable following rating reclassifications. Further, they find a rate changing lag of 1.5 years for all upgrades and downgrades that do not occur simultaneously with a company specific event. For downgrades accompanied by company specific events the adjustment period is less than 6 months. They conclude that equity markets account for all informational content associated with a rerating of a firm's debt in the month containing the rerating.

Griffin and Sanvicente (1982) criticize the methodological approach taken by Pinches and Singleton (1978) and suggest that this is the main reason for contrary results. Griffin and Sanvicente (1982) use 3 different methods for evaluating abnormal equity price adjustments; the one factor model, two factor cross sectional model and a model which "controls for nonevent or extraneous factors by exploiting the properties of the two factor model of equilibrium returns and constructing a portfolio where each asset is matched to an asset in the event portfolio." They also study re-ratings by Moody's and Standard and Poor's which could contribute to the different results when compared to Pinches and Singleton (1978). Results of their study indicate that bond rating changes do provide information to equity holders corresponding to stock returns, particularly for downgrades. However they stress that the main contribution of their work is in the critical assessment of methodologies used in examining the effect of rating changes of security prices.

2.4 Daily Stock Returns

Using daily stock returns in their analysis; Followill and Martell (1997), Dichev and Piotroski (2001) and Bannier and Hirsch (2010) all find significant negative reactions to downgrades. In contrast, Davidson et al. (1987) obtain significant reaction to upgrades as well as significant negative anticipatory effects which reversed following the announcement of a downgrade. Ederington and Goh (1993) produce results that partially support a reactionary response to downgrades. However they approach the issue in a different manner than the other studies using daily stock returns by including the reason for rating reclassification in their analysis. These studies are similar in that they use only ratings given by Moody's however their methodologies, results and datasets differed substantially.

Credit rating agencies provide a credit watch list or rating review which is designed to give indications of future rating changes as well as a shorter term indicator of credit worthiness than actual reclassifications. Followill and Martell (1997) test the effects of the announcement of both a review for a downgrade and for the announcement of an actual downgrade by Moody's Investor Services Incorporated. For both series of announcements the authors are able to distinguish between the wire release day and the financial press reporting day. Their data cover the period of December 1985 to May 1988. Followill and Martell (1997) find that downgrade announcements provide significant information if they are not preceded by a review announcement and that the information content of these downgrade announcements does not depend upon reports by the financial press. Specifically, announcements regarding reviews for downgrades show significant negative abnormal returns on the announcement date. However downgrade announcements only exhibit significant negative returns when they are not preceded by a review announcement.

Similarly Bannier and Hirsch (2010) provide a more comprehensive and recent approach in determining the informational content associated with the watch list. In a preliminary test they compare cumulative abnormal returns before and after the introduction of the Moody's watch list.[4] A significant break in the series is found with more negative cumulative abnormal returns in the post watch list period than in the pre watch list period. Additionally they consider how the watch list is used, testing whether it was used as an instrument to deliver information or as an implicit contract between rating agency and firm. They conclude that for a firm with high credit worthiness, the watch list is used as a means to convey precise and accurate information. Conversely for low credit firms the watch list is used as a tool for actively monitoring the given firm.

In another approach Dichev and Piotroski (2001) report results based on cumulative abnormal returns as well as buy and hold returns. They provide insight into the relationship between the price effect and the reference entity being a parent or subsidiary firm. Another significant strength of Dichev and Piotroski's work is that they use a much richer dataset than previous studies using stock returns. For example, comparing the pre-filtered number of re-rating/review announcements with the dataset employed by Followill and Martell (1997) we see that Dichev and Piotroski (2001) have 50 times the observations of Followill and Martell (1997). They report that downgrades are associated with significant negative abnormal returns, which are most prominent in the first month following the downgrade but could last up to one year.

Credit rating changes in bond and equity markets should not necessarily provide similar market price effects. In an effort to properly explain the effect of credit rating changes on equity markets Ederington and Goh (1993) incorporate the reason for the rating change announcement in their dataset. They argue that 'if

[4] On October 1st 1991 Moody's incorporated watchlist assignments as a type of rating action; this is where they test for the series break.

bonds are downgraded because the rating agencies foresee an increase in leverage that will transfer wealth from bondholders to shareholders, bond prices should fall but equity prices should rise' and therefore a downgrade resulting from an increase in leverage should result in an increase in equity price. They divide the reasons for rating changes into the following three categories: 1) Change in firm's earnings, cash flow, financial prospects or performance. 2) Actions that result in a change in leverage. 3) Miscellaneous or no reason given. From the standard market model they find a negative reaction to downgrades resulting from a revaluation of the firm's or industry's financial prospects on the event date and the day after the event. However no significant reaction is found for all other downgrades. In general they conclude that credit rating changes must not be thought of as possessing a homogeneous relationship with equity prices.

Davidson et al. (1987) is the only study relying on daily stock returns and reporting robust anticipatory price effects. Their dataset ranged from January 1977 to December 1981. In line with most other re-ratings literature, no significant anticipatory effects are detected with upgrades however they find significant negative abnormal equity returns following the announcement. This could be due to the reason given by Ederington and Goh (1993) above, meaning these upgrades could be due Moody's foreseeing a decrease in leverage that will transfer wealth from shareholders to bondholders and therefore have a negative effect on equity prices but a positive effect on bond prices. For downgrades they find both anticipatory and reactionary effects. Cumulative abnormal returns for the period between the event and 90 days prior to the event are significant and negative, whereas the 90 days following the announcement (i.e. day 1 to day 90) has a reversal of the post event decreases.

The previous section reviews literature focusing on the equity markets anticipation/response to credit rating changes. Review announcements have consistently been shown to provide informational value, specifically for downgrades. There have been only a few studies that find a significant reaction/anticipation to upgrades. However, valuable information can be obtained from these few studies as they employ methods or controls generally not considered in the literature.

2.5 Other significant works

There have been various other works investigating how ratings react to events that cause the microstructure of the credit ratings market to change. These events include; the addition of Fitch as major market player, regulation fair disclosure and Moody's rating class refinement. In general the focus of these papers was to investigate the informational content of credit rating changes after a given event. An event that can be shown to have a significant impact on the quality of credit ratings will play a key role in analyzing the evolving quality of corporate bond ratings. Therefore the following results could provide valuable insight. However our dataset does not cover observations before 1999 and hence Moody's rating class refinement will not influence the results.

The literature considered in this sub-section can be viewed as addressing economic theory regarding market competition. In a highly competitive market individual suppliers theoretically have very little or no control over the market price. At the other extreme a pure, unregulated, monopolist has considerable control over prices as they are the sole supplier in the industry under consideration. The credit ratings market in the US can best be described as an oligopoly, a market where a few firms dominate all other potential entrants. An increase in competition can theoretically lead to the following; decreases in prices, increased quality of offered product or service, reduction of information asymmetry and an overall increase in economic welfare. The following works essentially address this issue. Becker and Milbourn (2011) examine the effects of the Fitch Rating Agency's entrance (defined by their increase in market share of ratings) and Jorion et al. (2005) who study the effects of Regulation Fair Disclosure.

In a relevant article, Becker and Milbourn (2011), study the increased competitiveness of the credit rating market. They show that Fitch entered the credit rating market as a major player in early 2001.[5] They calculate market share as the total number of ratings issued by Fitch divided by the total number of ratings issued by Moody's, Standard and Poor's and Fitch combined. They examined how the quality of credit ratings changes as Fitch's market share increases. Using OLS and probit specifications, Becker and Milbourn test how the increase in Fitch's market share affect ratings given by Moody's and Standard and Poor's. They find that increases in market share are associated with increases in bond and firm ratings. They also test of the ability of ratings to predict default using a linear probability model where indicators of future default are regressed on ratings and control variables. They find a positive relationship between competition and the difference between investment grade and speculative grade default probabilities. In other words, as competition increases so does the gap between default probability of investment and speculative grade bonds. Thus the informational content of ratings appears to decrease with increases in competition.

If competition truly decreases the informative value of credit ratings then, from an economic standpoint, increased regulation seems to be the next best solution. According to the Securities Exchange Commission (SEC), Regulation Fair Disclosure (Regulation FD) was designed to address the issue of the selective disclosure of information in financial markets (SEC filing 2000). Before Regulation FD there were apparent problems of issuers releasing non-public information to certain investors. After implementation, any non-public information released by an issuer to an outside party must be publicly disclosed. Therefore, Regulation FD was designed in an effort to reduce information asymmetry among investors in the financial market.

[5] They find that by 2001 Fitch had a substantial share of issued ratings and therefore consider 2001 to be when they enter the market as a major player.

In order to minimize interference with businesses that are reliant on non-public information certain groups are exempt from regulation. The four categories for exclusion will be briefly outlined in what follows, a more thorough definition can be found in the SEC filing on Selective Disclosure and Insider Trading. The first exemption is any person who “owes the issuer a duty of trust or confidence,” for example an issuer’s accountant (SEC filing 2000). The second category for exemption includes persons who engage in business with the issuer and therefore require certain non-public information. The third category exempts credit rating agencies. Finally, Regulation FD “does not apply to disclosures made in connection with securities offering registered under the securities act,” (SEC filing 2000).

Jorion et al. (2005) address whether the implementation of Regulation FD changed the informational value of credit ratings. This is the only work we find that directly examines the relationship between Regulation FD and credit ratings. Using standard event study methodology, Jorion et al. (2005) calculate abnormal stock returns around re-rating dates. They study the period from August 1998 to December 2002 using ratings from Moody’s, Standard and Poor’s and Fitch. In order to analyze the change between periods they split their sample equally into two series each containing 26 months. Jorion et al. (2005) find, using the pre-regulation period, significant abnormal returns around downgrade events and no significant abnormal returns around upgrade events. In the post-regulation period they find both upgrades and downgrades to display significant abnormal returns, with downgrades showing a stronger response. Thus Jorion et al. (2005) conclude that Regulation FD increased the informational effects of rating changes.

Heflin et al. (2003) address how Regulation FD impacted the flow of financial information to capital markets preceding earnings announcements using firm data from First Call, CRSP and Compustat databases. They study quarterly data directly surrounding Regulation FD. They define their pre Regulation FD sample as the fourth quarter of 1999 and the first two quarters of 2000 and the post Regulation FD sample as the last quarter of 2000 and the first two quarters of 2001. Using standard event study methodology they find that absolute cumulative abnormal returns prior to earnings announcements are significantly larger pre Regulation FD then they are post Regulation FD. Therefore, they conclude that Regulation FD increased the efficiency of the flow of financial information.

2.6 CDS Market

Many previous studies use bond prices or yields in quantifying the informational content of credit ratings. However our research makes use of CDS spreads as they are already credit spreads. Hull et all (2004) note that to obtain credit spreads using bonds, yields and prices must be adjusted which requires an assumption regarding an appropriate risk free rate. They conjecture that probabilities calculated from historical data are usually less than the default probabilities backed out from bond prices. This is consistent with earlier work done on this subject. For example Altman (1989) investigates bond mortality and performance rates. He finds that corporate bonds, adjusted for impact of defaults, have a significant positive return spread above the US Treasury rates. Possible explanations for this discrepancy include; mispricing of corporate debt issues, liquidity risk and interest rate or reinvestment risk. Altman argues that some institutional investors can only legally buy investment grade bonds. Thus non-investment grade bonds could see reduced demand and inflated prices. Therefore CDS spreads should give a better measure of default probability and credit worthiness than bond prices or yields.

Preliminary work by Hull et al. (2004) compares CDS and bond markets and analyzes CDS market response to credit rating changes. In order to test the relationship between CDS and bond markets they exploit the following theoretical relationship;

$$CDS = (y - r)/(1 + A)$$

Where *CDS* = n-year CDS spread, *y* is the yield on an n-year par yield corporate bond, *r* is the yield on an n-year par yield riskless bond and *A* is the expected accrued interest on the par yield bond at the time of the default.

From this they estimate that the risk free rate lies between the 5-year swap rate and the 5-year Treasury bill rate. To analyze the effect of rating reclassifications on the CDS market Hull et al. first, test the change in CDS spreads conditional on ratings events then test the probability of a rating event occurring conditional on changes in the CDS spread. Their sample covers the period from 1998-2002. Six types of credit rating events are considered; downgrades, review for downgrades, negative outlooks, upgrades, review for upgrades and positive outlooks. Through event study methodology they find that the CDS market anticipates all negative credit events and that the CDS market fully adjusts by the day directly following the event. Consistent with the majority of previous research Hull et al. find no significant effects in relation to positive credit events.

In a comparable research, Norden and Weber (2004) analyze stock market and CDS market responses to credit rating changes. Their sample period spans 1998-2002, covering more than 1000 reference entities and includes following sectors; financials, telecoms, automotives, utilities, chemicals, retailers and other. Using event study methodology they show that both stock and CDS markets anticipate rating downgrades by approximately 60-90 days. They find asymmetric effects where negative rating events produce significant price effects but positive rating events do not. Comparing the CDS and equities market, they show that the CDS market leads the stock market in anticipating downgrades for all rating agencies. When analyzing different rating events within and across agencies they find that rating change reviews by S&P and Moody's provide significant abnormal returns whereas Fitch reviews do not. They also note that physical downgrades and upgrades do not result in significant anticipation or reaction in either market. Becker and Milbourn (2011) note that Fitch acquired a large portion of its market share in early 2001 and since Norden and Weber (2004) sample between 1998 and 2002, insignificant effects from Fitch re-ratings can be expected. It is reasonable to assume that a sample after mid 2001 would produce consistent results across all 3 ratings agencies.

Chapter III. Methodology

Non-stationary time series frequently arise in the analysis of financial markets. Improper estimation leads to inaccurate results and erroneous conclusions. However, there are several estimation methods such as vector error correction models that allow non-stationary variables and produce reliable results. In the following three subsections, methodological procedures and variables used for estimation are presented. The first subsection provides a description of vector autoregressive estimation, while the second describes vector error correction methods. Both subsections include models to be estimated. The final subsection defines all variables considered in estimation.

3.1 Vector AutoRegressive Methods

When modeling dynamic relationships between more than one variable, single equation models are insufficient. A typical method for estimating relationships between many endogenous variables is a vector autogressive (VAR) model. In a VAR each endogenous variable is regressed on lags of all endogenous variables included in the model and a set of control variables. Therefore in estimating a VAR the number of equations to be estimated will match the number of endogenous variables. Using vector notation a VAR of order p, VAR(p), is given by the following equations:

$$CDS_t = \alpha + \sum_{i=1}^{p} CDS_{t-i}\,\beta_i + \sum_{i=1}^{q} CR_{t-i}\,\zeta_i + \theta X_t\,\varepsilon_t \qquad (1)$$

$$CR_t = \kappa + \sum_{i=1}^{s} CR_{t-i}\,\varpi_i + \sum_{i=1}^{r} CDS_{t-i}\,\lambda_i + \gamma X_t\,\nu_t \qquad (2)$$

Where X_t is a vector of exogenous variables, CR_t measures credit ratings and CDS_t measures CDS spreads. β_i , θ, and ζ_i are coefficients on CDS spreads, exogenous variables and credit ratings respectively in equation (1). ϖ_i, λ_i and γ are matrices of coefficients to be estimated on lagged credit ratings, lagged CDS spreads and exogenous variables respectively in equation (2). ε_t and ν_t are vectors of innovations.

Equation (1) estimates the impact of lagged CDS spreads and credit ratings on current CDS spreads. Equation (2) estimates the impact of lagged CDS spreads and credit ratings on credit ratings. Since each equation contains only lags of each endogenous variable, simultaneity issues do not arise. Estimating each equation by OLS produces both the generalized least squares estimator and the maximum likelihood estimator assuming multivariate normal errors (Davidson and Mackinnon, 2004). We specify the number of lag orders using Akaike and Schwarz criterion.[6]

VAR specifications are commonly used to determine the lead lag relationship between endogenous variables. This is particularly useful since the focus of this research is to determine the quality of Issuer credit ratings. We argue that if CDS markets significantly lead rating changes, then the ratings information value and hence rating quality are low.

The focus of our analysis will be to determine the degree of variation in CDS spreads that can be explained by credit ratings and the degree of variation in credit ratings that can be explained by CDS spreads. For each estimated VAR we analyze the lead-lag relationship though variance decomposition. Variance decomposition measures the contribution of component shocks on the variance of each endogenous variable. This is done by calculating the forecast error of credit ratings and CDS spreads for a given horizon and determining the percentage that each innovation contributes.

3.2 Vector Error Correction Methods

A vector error correction (VEC) model is similar to a restricted VAR, however it allows for co-integration among non-stationary endogenous variables. Therefore

[6] If ratings from all agencies were included as endogenous variables in a single VAR severe multicollinearity would almost certainly be present, rendering the standard errors and test statistics unreliable. Therefore a separate VAR is estimated for each agency.

we estimate a VEC model for any cross section where ratings are co-integrated with CDS spreads and a VAR for the others. VEC models restrict the long-run behavior of the independent variables while allowing for short-run adjustments. The error correction representation regresses first differences of each endogenous variable on; lags of differenced dependent variables, explanatory variables and an error correction term. The error correction term, also known as the equilibrium error, is given by the co-integrating vector. A very general representation of the error correction model is given in Hamilton (1994). Consider that ratings and CDS spreads are I(1) (integrated of order 1) and suppose that they are co-integrated with co-integrating vector [1, - θ]. Further suppose the equilibrium error is denoted s_t. This implies that the subsequent three variables are stationary {I(0)}; $\Delta CDS_t = CDS_t - CDS_{t-1}$, $\Delta CR_t = CR_t - CR_{t-1}$, and $s_t = (CDS_t - \theta CR_t)$. This leads to the following model:

$$\Delta CDS_t = \beta' X_t + \gamma_1(\Delta CR_t) + \gamma_2(\Delta CR_{t-1}) + \gamma_2(\Delta CR_{t-2}) + \cdots + \gamma_{p-1}(\Delta CR_{t-d+1}) + \theta_1 \Delta CDS_{t-1} + \theta_2 \Delta CDS_{t-2} + \cdots + \theta_{p-1} \Delta CDS_{t-j+1} + \mu(s_t) + \varepsilon_t \quad (3)$$

$$\Delta CR_t = \beta' X_t + \delta_1(\Delta CR_t) + \delta_2(\Delta CR_{t-1}) + \delta_2(\Delta CR_{t-2}) + \cdots + \delta_{p-1}(\Delta CR_{t-l+1}) + \phi_1 \Delta CDS_{t-1} + \phi_2 \Delta CDS_{t-2} + \cdots + \phi_{p-1} \Delta CDS_{t-h+1} + \pi(s_t) + \eta_t \quad (4)$$

Equation (3) describes the variation in CDS spreads around their long run trend and Equation (4) describes the variation in credit ratings around their long run trend. X_t is a vector of exogenous variables, η_t and ε_t are vectors of innovations. This system is only internally consistent if credit ratings and CDS spreads are co-integrated. Therefore, assuming CDS spreads are co-integrated with rating changes, the above model can be applied. In order to analyze the contribution to price discovery we study variance decomposition as done for VAR specifications.

3.3 Factors Related to Credit Ratings

In this subsection we introduce the estimation variables and their theoretical or empirical reasons for inclusion. The majority of previous research assessing the relationship between credit rating changes and either stock, bond or CDS prices has relied on event study methodology and thus has no extensive list of explanatory variables. However, Vassalou and Xing (2004) suggest that when using stock returns there should be an adjustment in regards to size, book to market ratio and default risk. Naturally these variables, along with a few others, will initially be included in the vector of explanatory variables.

CDS Spread

In determining an appropriate benchmark to compare credit re-ratings, the previous literature uses three alternatives; bond markets, equity markets or CDS markets.[7] The CDS market is the best choice as addressed in Norden and Weber (2004) as well as Hull et al. (2004)[8]. Bond and equity prices are noisier measures of credit worthiness than CDS prices. We extract CDS spreads from Bloomberg, downloading all data available for the period of January 2000 to December 2011.

Size

The main finding of Vassalou and Xing (2004) is that size and book to market ratio (BMR in what follows) are directly related to the default risk of a firm. They find that default risk decreases monotonically as firm size increases. Therefore smaller sized firms can be expected to have a higher default risk than larger sized firms. We measure firm size using total assets shown on balance sheet. We download total assets from Compustat and Bloomberg, making certain that values are identical.

---

[7] Market is a term used to include; prices, returns, yields, or spreads from the given market.

[8] Hull et al. (2004) argue that once a CDS quote is given, the dealer is committed to trading the minimum principal at the quoted price, in contrast there is no commitment for a dealer to trade at a quoted bond price. They also point out that bond yields need to be transformed into credit spreads using a benchmark risk-free rate, whereas CDS spreads are already given as credit spreads and require no transformation.

Book to Market

As mentioned above, Vassalou and Xing (2004) show that the BMR of a firm is a key determinant of default risk. They classify 'value stocks' as high BMR equities and 'growth stocks' as low BMR equities. Their findings indicate that BMR is positively associated with the level of default risk. Therefore we include BMR in the set of independent variables. BMR is available from Compustat and from Bloomberg. We extract values from both databases and ensure that there are no discrepancies.

Credit Spread

Bloomberg defines a credit spread as the following: "the spread between Treasury securities and non-Treasury securities that are identical in all respects. For example the yield differential between the U.S. 10 year Treasury bond and the AAA rated 10 year corporate bond would be the credit spread."

For this analysis credit spread is defined as the difference in yield between Moody's Baa and Aaa Indices. The bonds included in these indices have maturities that are more than 20 years, are not susceptible to redemption and maintain their respective rating class (Baa or Aaa). In contrast to previously mentioned variables, and parallel to subsequent variables, credit spread is a market wide measure in that it is time specific as opposed to firm specific. Therefore credit spreads should be included as a control variable as they can provide a general sense of market conditions. We use Bloomberg to extract Moody's indices.

Term Spread/Interest Rate

Term spread can be defined as the difference between long and short maturities of a riskless bond. Both the short term interest rate and term spread can be viewed as a signal of economic activity. Short interest rates, controlled by monetary authorities, are usually high during expansions and low during recessions. Term spreads can be understood in terms of inflation rates. Higher term spreads should be associated with higher expectations of inflation. Therefore future economic expansion should be positively related to term spreads. For this analysis, term spread is defined as the absolute difference between the 30-year US Treasury Bond/Note and the 3-month US Treasury Bond/Note. We extract Treasury note data from Bloomberg.

Chapter IV. Sample Data and Descriptive Statistics

This section describes the process of data collection and gives a description of the final sample. The first subsection describes where each data item is acquired as well as criteria used in issuer selection. The second subsection provides a detailed description of the sample.

4.1 Data Collection

Due to the lack of quoted bond prices we focus on the relationship between CDS spreads and credit ratings. The sample selection procedure is as follows. Identifiers for all bonds listed on TRACE database between 2002 and 2010 are downloaded; the identifier being used is the 9 digit bond CUSIP. CUSIP numbers are provided by CUSIP Global Services (CGS) a firm specifically focused on providing identifiers for securities worldwide. CGS provides a 9-digit CUSIP identifier for issuers and their financial instruments traded in Canada and the U.S. The 9-digit CUSIP structure is designed so that each issuer and type of instrument can be easily identified. The first 6 characters represent the unique name of the issuer, where the issuer can be a company, municipality or government agency. The 7^{th} and 8^{th} characters represent the issue type, either equity or debt. The 9^{th} character checks the accuracy of the first 8 characters. All bonds found on TRACE are then matched with issuers found on COMPUSTAT using the first 6 characters. 36 129 bonds from 5717 issuers are listed on TRACE between 2002 and 2010. 13 263 issuers are listed on COMPUSTAT between 2003 and 2010. We then merge the datasets and keep only bonds issued by firms appearing in both datasets, which gives a sample of 8406 bonds issued by 1885 firms. Since the focus of this analysis is on the CDS market, only unique issuers are kept. Any issuer not domiciled in the US is eliminated; reducing the sample to 1720 issuers. Next, CDS tickers for each issuer are downloaded; if the issuer does not have an accompanying CDS then the issuer is eliminated from the sample leaving 862 unique issuers. For all available CDS tickers, spread data is downloaded for the sample period of 01/01/2000 to 01/01/2012. As was the case in the bond market, CDS spreads are not quoted on a daily basis. Therefore any CDS instrument missing more than 35% of its total observations is eliminated. Further, any CDS instrument with less than 75 total observed spreads is removed. This reduces the sample by 370, leaving 492 issuers. Historical ratings for each issuer given by Moody's, Standard and Poor's and Fitch are then handpicked from the Bloomberg Terminal. Any issuer experiencing less than 3 rating changes in the CDS sample period (01/01/2000 to 01/01/2012)[9] is removed from the sample leaving 400 issuers. Finally, after merging all CDS and rating data, all issuer's that do not experience at least two rating changes accompanied by quoted CDS spreads are dropped from the sample. The final sample consists of 246 unique issuers. CDS spreads and control variables are downloaded from the Bloomberg Terminal. Using bond CUSIP numbers, the associated 5 year CDS tickers are downloaded. This ensures that the CDS and bond are associated with the same issuer. CDS prices are taken from Bloomberg Valuation Service rather than TRACE because Bloomberg's prices are much more comprehensive.[10]

4.2 Sample Descriptive Statistics

This subsection provides descriptive statistics for the fully cleaned dataset. The first column of each panel in Table 1 reports the total number of upgrades and downgrades in the sample period. Panels A, B and C report statistics from Moody's S&P and Fitch samples respectively. It is quite obvious that firms face more credit rating downgrades than upgrades from all three rating agencies. This is consistent with previous work, and is more pronounced in larger more recent datasets. For example, Weinstein (1977) use a sample containing 72 downgrades and 60 upgrades

---

[9] This sample is not common for all CDS spreads, it is simply the sample period that was used for the data request. As noted the smallest sample contains 163 observations (approximately 7.5 months), the largest sample is 2570 observations (approximately 117 months).

[10] Both sources are assumed to be of reasonable quality.

from 1962 to 1974. It is worth noting that the difference between upgrades and downgrades can be accounted for by the final year of this sample (1974) where there are 26 downgrades and 11 upgrades. Davidson et al. (1987), using data from 1977 to 1981, obtain a dataset containing 93 downgrades and 69 upgrades. Ederington and Goh (1993) collect a dataset with 243 downgrades and 185 upgrades from the period spanning from 1984 to 1986. More recent research has the luxury of directly downloading time series data for rating changes, whereas early studies rely on hand-picked datasets from sources such as Bloomberg and Rating Agency Bond Guides and therefore are limited in size.[11] This is quite apparent when considering recent work by Bannier and Hirsch (2010). Their dataset covers the time period from 1982 to 2004 and contains 2531 downgrades and 1512 upgrades. When considering datasets taken from a variety of time periods, it is clear that downgrading historically dominates upgrading. This finding coincides with our dataset.

[Please insert table 1 about here]

Table 1 also presents the distribution of ratings changes by number of classes changed. A rating change of one class is defined as an upgrade or downgrade to an adjacent rating category. As we expected, the majority of rating changes occur over one or two categories. Changes across multiple categories occur much more frequently in downgrades than in upgrades. An obvious explanation for this is the well-defined state of default. When an issuer defaults their credit rating will drop immediately to the lowest grade which is default. Downgrades lead to this well-defined event and its associated cash flow problems. Reasons for upgrades across multiple categories may not be as obvious. An example of a multiple class upgrade from our sample is XTO Energy. On June 25th 2010 XTO Energy shareholders voted in favor of acquisition by Exxon Mobile Corporation (ExxonMobil) making them a

[11] Further some recent researchers do not have access to databases that allow series on rating changes to be directly downloaded and therefore must create their own dataset. This was the case for the dataset used in this paper.

wholly owned subsidiary of ExxonMobil. Moody's upgraded XTO Energy from Baa2 to Aaa following this announcement.

[Please insert table 2 about here]

Table 2 provides descriptive statistics for the firms included in the sample and the exogenous variables used in estimation. Panel A reports the distribution of firm characteristics described by the first two moments and minimum and maximum values. Three characteristics are included; total assets, total debt and total shares outstanding.[12] Values are reported in hundreds of thousands. The sample clearly contains a wide dispersion of firms based on the characteristics reported. This is shown by the high standard deviation as well as the large difference between minimum and maximum values. This result is consistent across the three characteristics examined.

Panel B provides the distribution of firms across sectors for the sample. The sector is listed in the first column with the number of issuers for each sector listed in the second column. The issuers in the sample come from a large variety of sectors. However, the distribution across sectors is unbalanced; almost half of the firms are from manufacturing, finance and insurance sectors.

Panel C describes the two exogenous variables used in estimation (credit spread and term spread). For each variable we report the first two moments and the minimum and maximum values. Further we provide the estimated correlation coefficient between the two variables. Both credit spread and term spread fluctuate between small intervals, 0.01 – 4.7 and 0.001 – 6.5 respectively,[13] however they move in opposite directions as shown by the negative correlation coefficient (-0.94).

[12] Data on firm characteristics come from COMPUSTAT, if values are missing Bloomberg data is used (when available).
[13] Values are given as yields.

Chapter V. Testable Hypotheses and Empirical Results

The following section provides a detailed description of hypotheses and results from empirical analysis. The first subsection details hypothesized relationships. The second subsection discusses the results using panel data methodology. Third, specification tests for VAR and VEC models are reported. The fourth and fifth subsections describe results using VAR regression techniques and VEC methods respectively.

5.1 Testable Hypotheses

Given the nature of the dataset several testable hypothesis arise. In this subsection two testable hypotheses are introduced and explained.

H_1: Credit ratings lag CDS spreads in adjusting for credit information.

H_2: Fitch has the lowest quality of corporate debt ratings.

Hull et al. (2004) and Norden and Weber (2004) have examined our first hypothesis. Their findings indicate that the CDS market anticipates negative credit events. They also find that CDS spreads can successfully predict the probability of changes in credit ratings. Therefore it is natural to hypothesize that CDS market leads credit ratings in price discovery. We examine variance decomposition to determine whether this hypothesis holds true. If credit ratings contribute a greater proportion to CDS variance than credit ratings contribute to CDS variance then we fail to reject this hypothesis.

The second hypothesis exploits the results from Becker and Milbourn (2011) who find that the entrance of Fitch as a major player in the credit ratings market resulted in lower quality of ratings. They measure rating quality in the following ways: the percentage of bonds rated AAA, the gap between investment grade and speculative grade bonds, correlation between bond yields and credit ratings (controlling for other factors) and the ability of credit ratings in predicting default.

Since bond issuers prefer higher ratings and rating agencies are paid by the firms which they rate, it seems reasonable to conjecture that under highly competitive situations agencies tend to assign higher ratings than they would otherwise. To measure default prediction they compare ratings and default events occurring within 3 years of a rating change. All three tests lead to the conclusion that decreased quality of credit ratings is associated with increased competition. Therefore it is hypothesized that in order for Fitch to gain its market share they necessarily have to inflate their ratings as a means of breaking the barriers of entering this market. Variance decomposition is compared across rating agencies in order to evaluate this hypothesis. If Fitch has the lowest quality of ratings, their ratings should contribute less to CDS spread variance than ratings from Moody's and S&P.

5.2 Empirical Results

The following subsections present the empirical findings of the current thesis. We start by documenting the relation between CDS spreads and lagged ratings. We then show the cointegration results followed by the VAR and VEC estimations of the two dependent variables.

5.2.1 Do ratings Influence the CDS? Preliminary Results

To test the relationship between credit ratings and CDS spreads we consider two preliminary tests. First, for each cross section included in our sample we examine the bivariate correlation coefficient. This provides a rough estimate of the linear association between CDS spreads and ratings. Secondly, we test whether changes in ratings cause the CDS spread to change through estimating the following panel one step ahead model.

$$CDS_t^{(j)} = \beta_0 + \beta_1 * CR_{i,t-1}^{(j)} + \beta_2 * CDS_{t-1}^{(j)} + \mu_t \qquad (5)$$

Where i = Moody's, S&P, Fitch; j = 1 to 246.

Table 3 provides correlations and estimation results from (5). Panels A, B and C report one step ahead estimation results using Moody's S&P and Fitch ratings respectively. Standard errors are computed using cross-sectional clustering. They are corrected for heteroskedasticity using White's method. We allow for fixed cross-sectional effects. We specify lag orders using the Akaike criterion. Panel D shows the correlations between ratings and CDS spreads. We report the mean correlation, standard error and associated p-value for each agency separately.

[Please insert table 3 about here]

The estimated models fit the data very well, as confirmed by the high R-squared values. Coefficient estimates for the first lag of CDS spreads are identical in all equations. They are significant and positive with magnitudes very close to 1.[14] Lagged credit ratings have statistically insignificant parameter estimates. In other words, yesterday's ratings are not related to today's CDS prices. Next we examine the relationship between current ratings and current CDS prices using correlation coefficients. The calculated correlation coefficient is below 0.1 for ratings issued from each agency. This implies that movements in credit ratings are not accompanied by movements in CDS prices. We can conjecture from this preliminary result that ratings do not influence future CDS prices.[15] Credit ratings do not convey material information that will cause prices to move. The following sections investigate further this issue by testing the mutual influences of both CDS prices and credit ratings. We consider both CDS prices and credit ratings as endogenous variables. We aim to investigate which among these variables causes the other to change.

---

[14] This result suggests that CDS spreads are probably following a random walk. The next section tests for the existence of unit root in the CDS series.

[15] Ratings Granger cause CDS spreads if Ratings help to forecast CDS spreads, given past CDS spreads. Our VAR models estimate jointly; whether Credit Ratings Granger cause CDS spreads and whether CDS spreads Granger cause Credit Ratings

5.2.2 Are Credit Ratings Co-integrated with CDS Spreads?

In this section, we first test whether CDS spreads and credit rating are co-integrated of order one. As a starting point, we perform Augmented Dickey Fuller unit root tests on each endogenous variable. If an issuer experiences very few rating changes in the sample period then the unit root test cannot be performed due to lack of variation in the variable being tested. We conduct the test on the level and include an intercept in the intermediate test equation. The number of lags is specified using Schwarz information criterion. We use various subsamples and different exogenous variables. The results are robust to all of these alternative specifications.

Moody's full sample data allows us to test 121 cross sections for a unit root. 96 out of 121 cross sections exhibit a unit root. S&P results indicate that 199 out of 225 cross sections contain unit root processes. Clearly S&P ratings vary significantly more than Moody's ratings. Fitch ratings data allow for 171 unit root tests to be executed, where 167 confirm unit root processes. These results indicate that ratings data from each agency contain unit root processes.

Using full sample results, approximately 70% of our sample firms issue CDS whose spreads contain unit root processes. However, this may not be representative of the issuers in our sample. Our data request for CDS spreads collects all relevant data between January 1st 2000 and December 31st 2011. Many CDS contracts were initiated between 2003 and 2005; therefore spread data contained in the first half of the sample is much less complete than spread data contained in the second half. Results from the second half of the sample should therefore be more representative of the true sample. Approximately 85% of CDS spreads in the second half of the sample indicate unit root processes. Therefore we confirm our finding in section 5.2.1 that CDS spreads contain non-stationary unit root processes.

We now conduct joint unit root and cointegration tests between CDS prices and credit ratings using Johansen's tests. Table 4 summarizes the results for five possible specifications. Each specification makes different assumptions regarding the trend underlying the data. Panels A, B and C provide Moody's S&P and Fitch related results.

[Please insert table 4 about here]

S&P full sample results (Panel B) specify approximately 89 ratings series are co-integrated with CDS spreads, whereas the first half of the sample specifies that approximately 40 series are co-integrated. We report similar results for Moody's and Fitch data. S&P tests provide the strongest support for co-integration between ratings and CDS spreads. Concentrating on S&P full sample results; 90 different pairs have ratings that are co-integrated with CDS spreads. Moody's and Fitch ratings results, (Panels A and C respectively) indicate that 41 and 68 ratings series are co-integrated with CDS spreads respectively. Co-integration tests suggest that VAR specification may be more appropriate then VEC to assess the mutual influence between the CDS prices and the credit ratings. In the next two sections, we will present the results for VAR and VEC estimation respectively.

5.2.3 Results from VAR Analysis

For each issuer in the sample whose ratings data do not exhibit co-integration with CDS spreads, we estimate a VAR model as in (1) and (2). Credit ratings and CDS spreads are specified as endogenous variables. We estimate ratings issued by each agency separately and, as in previous tests, we use variations of exogenous variables. Lag length for each VAR is selected through Akaike and Schwarz criterion including a maximum of four endogenous lags. For each issuer we estimate a separate VAR model. As a robustness check we estimate each VAR using five different sample periods; full sample, pre 2006, post 2006, pre 2008 and post 2008. Given the relative invariability of issuer ratings some cross sections do not lead to feasible estimation. This is sensitive to the number of exogenous variables included, the number of lags specified and the sample period selection.

Reported results include two exogenous variables which are credit spread and term spread for each VAR model. Short term interest rates are excluded in order to mitigate the multicollinearity problem. Since term spread is defined as the difference between 30-year US Treasury Bonds and 3-month US Treasury Bonds it can certainly be expressed as a linear function of short term interest rates. Table 5 shows the VAR estimation results.

[Please insert table 5 about here]

Panels A, B and C report results using Moody's, S&P and Fitch credit ratings respectively. The first equation in each panel regresses CDS spreads on control variables and lags of ratings and CDS spreads. The second equation regresses credit ratings on control variables and lags of CDS spreads and credit ratings. The table reports output using the full sample period. Mean values are the cross-sectional average of coefficient estimates.

Lagged CDS coefficient estimates from the first equation are significant for the first two lags. This reconfirms the autoregressive nature of CDS spreads found from the panel data estimation. The coefficient on the first lag of CDS spreads is significant in all estimated regressions and has a mean value slightly greater than 1. This result is robust to sample period selection and is consistent across ratings agencies. The coefficient on the second lag of CDS spreads is estimated as negative in approximately 66% of regressions. The mean is approximately -0.1 and is significant using S&P and Fitch credit ratings but not Moody's. Higher order lags of CDS spreads are estimated significantly in roughly 50% of equations. However coefficients are not consistent for different cross-sections. One exception is the third order CDS lag in the first equation for Moody's VAR (-0.037). The means are similar for Moody's and S&P ratings, however they are insignificant. Therefore CDS spreads clearly exhibit strong autoregressive processes of order 2. Lags of credit ratings are not highly significant; approximately 23% of first order lags were estimated as significant. Significant coefficient values are estimated as positive. A positive coefficient implies that CDS spreads have a positive relation with lower credit ratings; therefore a downgrade (upgrades) would result in CDS spreads increasing (decreasing).[16] Higher order lags of credit ratings produce insignificant results. Mean values have high p-values and thus are not very reliable. Therefore credit ratings do not seem to influence CDS spreads and CDS spreads do not seem to influence credit ratings. Instead, CDS spreads are influenced most by past CDS spreads and credit ratings are influenced most by past credit ratings.

The exogenous variables in the first equation are significant in approximately 25% of estimated regressions. The mean coefficient estimate for credit spread is negative and is significant only when using S&P ratings. The mean coefficient for term spread coefficient is insignificant in all specifications. Therefore it appears that an increase in the gap between the yield on low and high quality bonds is associated with decreases in CDS spreads. This result is puzzling since the credit spread is supposed to account for overall economic conditions, where wider credit spreads are associated with economic slowdowns and narrow credit spreads are associated with economic prosperity.

The second equation determines what factors influence credit ratings. First order lags of CDS spreads are mostly not significant. Higher order lags are also relatively insignificant. Therefore it does not appear that past CDS spreads influence current credit ratings. First order lags of ratings in the second equation are significant and positive. The mean value is significant and close to 1, results are consistent across rating agencies. Higher order lags are not statistically significant. Therefore credit ratings appear to be influenced by past ratings alone.

In order to fully examine the lead-lag relationship between CDS spreads and credit ratings, we consider the variance decomposition. Variance decomposition examines the forecast error variance of each endogenous variable in a VAR. The variation in each endogenous variable is separated into contributions from each of the two endogenous variables. Using variance decomposition we can determine the

[16] By definition, high numeric credit rating implies low credit quality.

proportion of CDS variance explained by credit ratings and CDS itself. If variation in CDS spreads is explained by past credit ratings then it can be concluded that ratings lead CDS spreads and hence ratings are informative. However if the opposite is true, i.e. rating variance is mostly contributed to through CDS, we conclude that CDS spreads lead ratings. Table 6, 7 and 8 report 10-period forecast error variance decomposition for Moody's S&P and Fitch respectively. We report contributions to variance in percentages. Cross-sectional mean, standard errors and p-values are calculated in the same manner as for the VAR output.

[Please insert table 6 about here]

The results from Table 6 indicate that Moody's ratings do not contribute much to CDS variation. The first period contributions indicate that 0% of the variation in CDS spreads is contributed to by ratings. The result is similar when looking at different forecast periods. When examining credit ratings variance, we find contributions of CDS spreads to ratings variance are also very small. One period forecast results show that Moody's ratings variation is explained primarily by past ratings. However as the forecast period is increased CDS spreads do contribute to a small proportion of ratings variance (6.3% in the 10th period). Therefore we conclude that the variability in CDS spreads is explained solely by past CDS spreads and that the majority of variation in Moody's ratings is explained by past ratings. We also conclude that, on the margin, CDS spreads appear to contribute more to Moody's ratings variance than ratings contribute to CDS variance.

[Please insert tables 7 and 8 about here]

S&P (Table 7) and Fitch (Table 8) results are similar to those reported for Moody's. S&P and Fitch ratings both contribute very little to the variation in CDS spreads. However, in comparison to Moody's, CDS contribution to S&P and Fitch ratings are approximately twice as large. Similar to Moody's results, CDS spreads contribute to a negligible proportion of variation in S&P and Fitch ratings. These findings lead to two main results. First, CDS spreads are explained entirely by past CDS spreads. Second, ratings are explained primarily by past ratings. We further suggest that S&P and Fitch ratings may contribute more than Moody's does to CDS variation, though the results are marginal. Also CDS spreads may contribute to variations in credit ratings from each agency.

5.2.4 Results for Co-integrated CDS and Credit Ratings

For any issuer whose ratings show co-integration with CDS spreads we estimate a VEC model. We specify the number of co-integrating equations from the Johansen Co-integration test. The results are reported in a format identical to that used for VAR results. We estimate a difference VEC for each cross section separately and for each of the 5 sample periods. We specify lag length for each regression using Akaike and Schwarz criterion.[17]

Table 9 reports the results from VEC estimation. Panels A, B and C contain Moody's S&P and Fitch results respectively. Each estimated equation contains an intercept, two exogenous variables (credit spread and term spread), a co-integration parameter and lagged first differences of credit ratings and CDS spreads. The 1st equation specifies first differences of CDS spreads as the dependent variable. The 2nd specifies first differences of credit ratings as the dependent variable.

[Please insert table 9 about here]

Moody's results (panel A) for the first equation show that lags of CDS spreads are significant in most regressions. Coefficients for lagged ratings are insignificant in a large proportion of regressions. The results from the first equation indicate that CDS spreads are influenced by previous CDS spreads but not by past ratings. This is consistent with VAR results. Equation 2 results are not highly significant. Lagged CDS

[17] Lags order is therefore not consistent over cross sections, hence the difference in total estimated coefficients. (See Table 9). We specify a maximum of 4 lags.

spreads are insignificant in the most regressions and lagged credit ratings are insignificant in nearly all estimated regressions. This suggests that ratings are not influenced by prior CDS spreads or by past credit ratings.

S&P results (panel B) for equation 1 show coefficients for lagged CDS spreads are significant. Therefore CDS spreads are influenced by past CDS spreads. Coefficients for lagged credit ratings are significant in approximately 25% of estimated regressions. Therefore CDS spreads are not highly influenced by past credit ratings. Exogenous variables are significant in only 40% of estimated regressions. Equation 2 results are similar to those obtained using Moody's ratings. CDS spread and credit ratings coefficients are not significantly different from zeros. Therefore S&P VEC estimation results indicate that CDS spreads are influenced by past CDS spreads alone and that past CDS spreads do not influence credit ratings. This is consistent with VAR results. However, contrary to VAR results, VEC results indicate current credit ratings are not significantly influenced by their prior value.

Fitch results (panel C) for equation 1 indicate significant coefficients on the first two lags of CDS spreads and significant. Coefficients for lags of credit ratings are not significant in the majority of regressions. This coincides with earlier results. Therefore it appears that CDS spreads are influenced only by past CDS spreads. Term spread and credit spread coefficients do not appear to be significant. Identical to Moody's and S&P results, Fitch Equation 2 estimates are insignificant. This implies that credit ratings are not influenced by prior CDS spreads or prior credit ratings.

To further examine the lead-lag relationship between CDS spreads and credit ratings we analyze forecast error variance decomposition for each VEC. The results are presented in Tables 10, 11 and 12 for Moody's, S&P and Fitch respectively. The formats of Tables 10-12 are identical to those of Tables 6-8 (variance decomposition of VAR).

[Please insert table 10 about here]

Table 10 reports variance decomposition results from Moody's VEC estimation. The results are similar to those found from VAR variance decomposition. Moody's ratings do not contribute to the variation in CDS spreads and CDS spreads contribute a marginal portion to ratings variance. The first period contribution of CDS spreads to ratings is larger in comparison to VAR results. The contribution is however still less than 1%. Therefore VEC variance decomposition results confirm our previous findings that CDS spread variability is completely explained by past CDS spreads and that credit ratings variation is primarily explained by past credit ratings.

[Please insert tables 11 and 12 about here]

Results for S&P and Fitch are again identical to Moody's results. The first period contributions indicate that 0% of the variation in CDS spreads is explained by credit ratings. This proportion increases slightly when the forecast period is increased. When we examine ratings variance we find similar results. Our results show that variations in S&P and Fitch ratings are explained almost entirely by their past values. Thus we find that VEC variance decomposition results confirm the two major results found from VAR results; CDS spreads are explained entirely by past CDS spreads and ratings are explained primarily by past ratings. We note however that for the three tables 10, 11 and 12 mean values of the sixth column are systematically higher than those in the fourth column. In other words the CDS prices contribution to credit rating formation is always higher than the credit rating contribution to the CDS price formation even if both are economically marginal. The same conclusion was reached from Tables 6, 7 and 8.

Chapter VI. Conclusion

This research examines the relationship between credit ratings and CDS spreads in order to assess the quality of corporate ratings. A rating agency's primary responsibility is to provide information regarding the credit worthiness of their rated issuers and securities. This reduces uncertainty while increasing the information flow between investors and issuers. We question whether there is any information content in credit ratings that is not already publicly available. Previous research on bond rating changes focuses on bond and equity reactions. Most find significant effects associated with only downgrades. A few studies have incorporated CDS markets into their analysis. We prefer CDS spreads instead of bond yields for two reasons. First data on CDS prices for specific issuers are more reliable than data on bonds prices. Bond yields are more likely to be stale since for most bonds the market is completely illiquid. Second, CDS prices are more closely related to credit and default risk than yields.

In contrast to previous studies which use event studies, we specify VAR and VEC models. A major advantage of estimating VAR and VEC models is the ability to study the lead-lag relationship between endogenous variables. We initially assume that credit ratings are co-integrated with CDS spreads. However Johansen's Co-integration test results indicate that co-integration is present in less than half of the cross sections. For issuer's whose ratings exhibit co-integration with CDS spreads we employ VEC methods. VAR methods are used for issuer's whose ratings are not co-integration with CDS spreads.

VAR results confirm that CDS spreads and credit ratings are greatly influenced by their respective histories. VEC results for CDS spreads are identical. We analyze the variance decomposition for VAR and VEC models in order to understand the lead-lag relationship between credit ratings and CDS spreads or the relative contribution of each variable in the innovation of both endogenous variables. We find that CDS spreads are explained almost entirely by previous CDS spreads and that credit ratings are explained primarily by past credit ratings. Further, we find that

S&P ratings contribute slightly more to CDS variation than Moody's and Fitch ratings. Therefore S&P ratings may be more informative than Moody's and Fitch ratings.

Our VAR and VEC models show that credit ratings and CDS spreads are, for the most part, unrelated. Therefore credit ratings provide little information value to financial market participants. In regards to any differences in quality amongst agencies, we conclude that S&P may provide higher quality ratings than Moody's and Fitch. However this difference is small or even negligible. These findings are not surprising given the speculation regarding the quality of credit ratings. It seems likely that the majority of information conveyed through credit ratings is publicly available.

The results have serious implications for financial markets. If credit ratings do not provide investors with any information that is not already publicly available then why should they be considered? Firms issuing bonds generally require their bonds to be rated in order for them to be traded. Furthermore, the price or yield at which bonds trade is a function of the issuer's credit standing. Therefore inflated (deflated) credit ratings can lead to deflated (inflated) bond yields.

Regardless of ratings accuracy many institutional investors and portfolio managers are required to hold only bonds rated at investment grade or higher. The inability of rating agencies to anticipate the effects of financial crises has led to severe criticism of ratings quality. Our research suggests that perhaps this criticism is warranted. Further research could expand on this work by incorporating a larger number of issuers in the sample with quoted CDS spreads who experience several rating changes.

References

Altman, E.I., (1989). Measuring Corporate Bond Mortality and Performance. *Journal of Finance* 44, 902-22.

Bannier, C., Hirsch, C., (2010). The Economic Function of Credit Rating Agencies – What Does the Watchlist Tell us? *Journal of Banking and Finance* 34, 3037-3049.

Becker, B., Milbourn, T., (2011). How Did Increased Competition Affect Credit Ratings? *Journal of Financial Economics* 101, 493-514.

Clauretie, T., Glascock, J., Wansley, J., (1992). Institutional Bond Pricing and Information Arrival: The Case of Bond Rating Changes. *Journal of Business Finance and Accounting* 19, 733-750.

Campbell, D., Moore, M., (2012). Credit Suisse Cut Three Levels as Moody's Downgrades Banks. Bloomberg. http://www.futuresmag.com/2012/06/22/credit-suisse-cut-three-levels-as-moodys-downgrade?eNL=4fe38141150ba01b7300001a&utm_source=MarketWeekender&utm_medium=eNL&utm_campaign=FUT_eNL&_LID=120855091&page=4.

Davidson, R., MacKinnon, J., (2004). Econometric Theory and Methods. *New York: Oxford University Press, Inc*.

Davidson, W., Glascock, J., Henderson, G., (1987). Announcement Effects of Moody's Bond Rating Changes on Equity Returns. *Quarterly Journal of Business and Economics* 26, 67-78.

Dichev, I., Piotroski, J., (2001). The Long-run Stock Returns following Bond Ratings Changes. *Journal of Finance* 56, 173-203.

Ederington, L., Goh, J., (1993). Is a Bond Rating Downgrade Bad News, Good News, or No News for Stockholders? *Journal of Finance* 48, 2001-2008.

Followill, R., Martell, T., (1997). Bond Review and Rating Announcements: An Examination of Informational Value and Market Efficiency. *Journal of Economics and Finance* 21, 75-82.

Grier, P., Katz S., (1976). The Differential Effects of Bond Rating Changes on Industrial and Public Utility Bonds by Maturity. *Journal of Business* 49, 226-239.

Griffin, P.A., Sanvicente, A.Z., (1982). Common Stock Returns and Rating Changes: A Methodological Comparison. *Journal of Finance* 37, 103-120.

Heflin, F., Subramanyam, K., Zhang, Y., (2003). Regulation FD and the Financial Information Environment: Early Evidence. *Accounting Review* 78, 1-37.

Heinke, V., Steiner, M., (2001). Event Study Concerning International Bond Price Effects of Credit Rating Actions. *International Journal of Finance and Economics* 6, 139-157.

Hite, G., Warga, A., (1997). The Effect of Bond-Rating Changes on Bond Price Performance. *Financial Analysts Journal* 53, 35-51.

Hull, J., Predescu, M., White, A., (2004). The Relationship Between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements. *Journal of Banking and Finance* 28, 2789-2811.

Jorion, P., Liu, Z., Shi, C., (2005). Informational Effects on Regulation FD: Evidence from Rating Agencies. *Journal of Financial Economics* 76, 309-330.

Katz, S., (1974). The Price Adjustment Process of Bonds to Rating Reclassifications: A Test of Bond Market Efficiency. *Journal of Finance* 29, 551-559.

Norden, L., Weber, M., (2004). Information Efficiency of Credit Default Swap and Stock Markets: The Impact of Credit Rating Announcements. *Journal of Banking and Finance* 28, 2813-2843.

Pinches, G., Singleton, J., (1978). The Adjustment of Stock Prices to Bond Rating Changes. *Journal of Finance* 33, 29-44.

United States Securities and Exchange Commission (2000). Final Rule: Selective Disclosure and Insider Trading, *Exchange Act Release No.* 33-7881 (Oct. 23, 2000), htt://www.sec.gov/rules/final/33-7881.htm.

Vassalou, M., Xing, Y., (2004). Default Risk in Equity Returns. *Journal of Finance* 59, 831-868.

Weinstein, M., (1977). The Effect of a Rating Change Announcement on Bond Prices. *Journal of Financial Economics* 5, 329-350.

Table 1. Total Upgrades/Downgrades

This table provides information on the distribution of upgrades and downgrades by the three rating agencies included in the study; Moody's, Standard and Poor's and Fitch. All rating changes occur between January 1st 2000 and December 31st 2011. An upgrade is defined as any positive change in credit rating. A downgrade is defined as any negative change in credit rating. Panels A,B and C report the distribution of; all rating reclassifications, downgrades and upgrades respectively. The first column of each panel lists the number of rating categories changed in the rating change. The second, third and fourth column provide the number of reclassifications from Moody's, S&P and Fitch respectively.

Number Classes Changed	Panel A. Moody's			Panel B. S&P			Panel C. Fitch		
	Total	Upgrades	Downgrades	Total	Upgrades	Downgrades	Total	Upgrades	Downgrades
1	271	108	163	651	204	447	464	170	294
2	87	14	73	186	48	138	108	35	70
3	17	3	14	44	7	37	30	7	23
4	2	1	1	21	4	17	13	4	9
5	3	2	1	18	8	10	4	1	3
6	1	0	1	6	5	1	4	1	3
7	0	0	0	8	6	2	1	0	1
8	1	1	0	4	2	2	2	1	1
9	0	0	0	0	0	0	2	2	0
10	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0
>14	0	0	0	0	0	0	0	0	0

Table 2. Issuer Descriptive Statistics

This table reports descriptive statistics for issuer's contained in the sample and exogenous variables used in estimation. Panel A describes the sample; minimum, maximum, mean and standard deviation of issuer total assets, total debt and shares outstanding are reported. All values are in hundred thousands. Panel B reports the different sectors included in the issuer sample. NAICS classes were downloaded from naics.com using NAICS codes obtained from Bloomberg. The first column lists the different categories, the second column lists the percentage of issuers in the sample belonging to each category. Panel C provides the minimum, maximum, mean and standard deviation of the two exogenous variables (Credit Spread and Term Spread) as well as the correlation between them.

Panel A. Issuer Descriptives

Statistic	Total Assets	Total Debt	Shares Outstanding
Mean	22688.99	11214.98625	479.19
Min.	20.88	0.06	0.001
Max.	1121192	835300	8069.54
Stdev.	93266.71	39798.45	752.13

Panel B. Issuer NAICS Classification

Industry	Proportion of Issuers
Manufacturing	0.32
Agriculture, Forestry, Fishing and Hunting	0.01
Utilities	0.11
Mining, Quarrying, and Oil and Gas Extraction	0.05
Construction	0.03
Wholesale Trade	0.02
Retail Trade	0.09
Transportation and Warehousing	0.04
Information	0.08
Finance and Insurance	0.17
Real Estate and Rental and Leasing	0.02
Professional, Scientific, and Technical Services	0.03
Administrative and Support and Waste Management and Remediation Services	0.01
Health Care and Social Assistance	0.01
Accommodation and Food Services	0.02

Panel C - Exogenous Variable Descriptive Statistics

Statistic	Credit Spread	Term Spread
mean	2.54	2.32
std dev	1.57	2.03
min	0.01	0.00
max	4.69	6.49
correlation coefficient	-0.94	

Table 3. One Step Ahead Estimation of CDS using lagged ratings

This table provides results from regressing CDS spreads on lagged credit ratings. Panels A, B and C report results using Moody's, S&P and Fitch ratings respectively. We estimate the panels with cross-section fixed effect. We use the Akaike criterion to set the number of lags for both the ratings and CDS variables. For each variable; coefficient estimates, standard errors and p-values are calculated and shown in columns 2, 3 and 4 respectively. Standard errors are computed using White cross-section correction. Further, we report correlations between ratings and CDS spreads, shown in Panel D. For each issuer in the sample, we estimate the correlation between ratings and CDS spreads. We calculate and report the average correlation for ratings from each agency separately as well as the standard error of the mean and associated p-value.

Panel A. Moody's Ratings			
Variable	Estimate	Std. Error	P-value
Constant	2.270	1.074	0.03
Ratings (-1)	-0.149	0.120	0.21
CDS spread (-1)	0.997	0.003	0.00
Adjusted R-squared	0.996		
Akaike Criterion	9.476		
Log likelihood	-688869		
Panel B. S&P Ratings			
Variable	Estimate	Std. Error	P-value
Constant	-1.822	1.208	0.13
Ratings (-1)	0.259	0.154	0.09
CDS spread (-1)	0.998	0.002	0.00
Adjusted R-squared	0.996		
Akaike Criterion	9.643		
Log likelihood	-1542258		
Panel C. Fitch Ratings			
Variable	Estimate	Std. Error	P-value
Constant	1.103	0.629	0.08
Ratings (-1)	-0.059	0.090	0.51
CDS spread (-1)	0.998	0.003	0.00
Adjusted R-squared	0.996		
Akaike Criterion	9.145		
Log likelihood	-1204120		
Panel D. Correlation Between Ratings and CDS			
	Moody's	S&P	Fitch
Mean	0.064	0.083	0.097
SE(mean)	0.042	0.043	0.045
p-value	0.07	0.03	0.02

Table 4. Johansen Co-integration Tests

This table provides results from Johansen's Co-integration tests between CDS spreads and ratings from each agency. Panel A reports results for Moody's, panel B provides S&P results and panel C reports Fitch results. The results are for the entire sample. The first column in each panel lists the number of co-integrating vectors. Columns 2 through 6 provide the tests results allowing for different assumptions regarding the trend underlying the data. Columns 2 and 3 assume that there is no deterministic trend in the data, column 2 results specify no intercept and no trend in the co-integrating equation and test VAR whereas column 3 results estimate an intercept in the co-integrating equation. Columns 4 and 5 allow for a deterministic trend in the underlying data. Column 4 results are based on a co-integrating equation and test VAR each estimated with an intercept and no trend, whereas the fifth column estimates assume there is a trend factor in the co-integrating equation. Column 5 reports results allowing for a quadratic deterministic trend in the underlying data. An intercept and trend are entered into the co-integrating equation, a linear trend factor is included in the test VAR.

Panel A. Moody's Full Sample Results	Assume No Deterministic Trend	Assume No Deterministic Trend	Allow For Linear Deterministic Trend in Data	Allow For Linear Deterministic Trend in Data	Allow For Quadratic Deterministic Trend in Data
Number of Cointegrating Vectors	No Intercept No Trend in CE or test VAR	Intercept, No Trend in CE - No Intercept in VAR	Intercept, No Trend in CE and Test VAR	Intercept and Trend in CE - No Trend in VAR	Intercept and Trend in CE – Linear Trend in VAR
0	206	207	199	208	198
1	41	33	26	34	24
2	0	7	22	5	25
3	0	0	0	0	0
Panel B. S&P Full Sample Results	Assume No Deterministic Trend	Assume No Deterministic Trend	Allow For Linear Deterministic Trend in Data	Allow For Linear Deterministic Trend in Data	Allow For Quadratic Deterministic Trend in Data
Number of Cointegrating Vectors	No Intercept No Trend in CE or test VAR	Intercept, No Trend in CE - No Intercept in VAR	Intercept, No Trend in CE and Test VAR	Intercept and Trend in CE - No Trend in VAR	Intercept and Trend in CE – Linear Trend in VAR
0	157	163	149	171	150
1	88	70	58	61	38
2	2	14	40	15	59
3	0	0	0	0	0
Panel C. Fitch Full Sample Results	Assume No Deterministic Trend	Assume No Deterministic Trend	Allow For Linear Deterministic Trend in Data	Allow For Linear Deterministic Trend in Data	Allow For Quadratic Deterministic Trend in Data
Number of Cointegrating Vectors	No Intercept No Trend in CE or test VAR	Intercept, No Trend in CE - No Intercept in VAR	Intercept, No Trend in CE and Test VAR	Intercept and Trend in CE - No Trend in VAR	Intercept and Trend in CE – Linear Trend in VAR
0	179	190	175	190	168
1	67	48	39	50	32
2	1	9	33	7	47
3	0	0	0	0	0

Table 5. VAR Estimation Results

This table reports VAR estimation results done in levels. Panel A shows estimates from the model containing Moody's ratings and CDS spreads as endogenous variables. Panel B provides results from specifying S&P ratings and CDS spreads as endogenous variables and Panel C reports estimates from a model specifying Fitch ratings and CDS spreads as endogenous variables. All models include two control variables; credit spread and term spread. Credit spread is defined as the difference in yield between prime rated bonds (AAA, Aaa) and investment grade bonds (BBB-, Baa3). Term spread is defined as the difference in yield between 30-year US Treasury Bond/Note and the 3-month US Treasury Bond/Note. Equation 1 in each panel specifies CDS spreads as the dependent variable, equation 2 specifies ratings as the dependent variable. Mean values are calculated by taking the arithmetic average of each estimate for that specific period. Standard errors are defined as the mean value divided by the square root of total observations. P-values are then calculated using the Student's t-distribution.

Panel A. Moody's Full Sample Results										
Equation 1	CDS(-1)	CDS(-2)	CDS(-3)	CDS(-4)	Ratings(-1)	Ratings(-2)	Ratings(-3)	Ratings(-4)	Credit Spread	Term Spread
Mean	1.036	-0.0808	-0.0352	0.000325	5.082	-18.266	21.526	-9.102	-1.934	-0.852
SE(mean)	0.0311	0.0585	0.0307	0.0317	3.0262	14.682	16.12	9.336	1.631	1.827
P-value	0.000	0.180	0.270	0.992	0.100	0.226	0.202	0.351	0.241	0.643
% significant	1	0.913	0.467	0.455	0.245	0.087	0.2	0.0909	0.327	0.224
# of positive and significant	49	7	2	2	11	1	2	0	4	2
# of negative and significant	0	14	5	3	1	1	1	1	12	9
Total	49	23	15	11	49	23	15	11	49	49
Equation 2	CDS(-1)	CDS(-2)	CDS(-3)	CDS(-4)	Ratings(-1)	Ratings(-2)	Ratings(-3)	Ratings(-4)	Credit Spread	Term Spread
Mean	-1.02E-08	0.0002	-0.0002	-0.000039	0.995	0.00107	0.00284	0.002996	0.00408	0.00573
SE(mean)	0.000154	0.000281	0.000217	0.00024	0.000938	0.000807	0.00162	0.00116	0.00135	0.0067
P-value	1.000	0.481	0.480	0.873	0.000	0.199	0.099	0.026	0.004	0.396
% significant	0.408	0.087	0.0667	0.0909	1	0	0	0	0.367	0.34
# of positive and significant	11	1	0	1	49	0	0	0	12	11
# of negative and significant	9	1	1	0	0	0	0	0	6	5
Total	49	23	15	11	49	23	15	11	49	47

Panel B. S&P Full Sample Results										
Equation 1	CDS(-1)	CDS(-2)	CDS(-3)	CDS(-4)	Ratings(-1)	Ratings(-2)	Ratings(-3)	Ratings(-4)	Credit Spread	Term Spread
Mean	1.095	-0.136	-0.028	-0.018	6.349	-9.064	0.914	-1.578	-1.280	0.786
SE(mean)	0.020	0.033	0.019	0.019	3.566	8.102	7.468	2.769	0.397	0.819
P-value	0.000	0.000108	0.148	0.368	0.078	0.267	0.903	0.573	0.002	0.339
% significant	1	0.794	0.558	0.643	0.228	0.190	0.154	0.071	0.238	0.267
# of positive and significant	101	16	10	4	22	4	2	0	2	6
# of negative and significant	0	34	19	14	1	8	6	2	22	21
Total	101	63	52	28	101	63	52	28	101	101
Equation 2	CDS(-1)	CDS(-2)	CDS(-3)	CDS(-4)	Ratings(-1)	Ratings(-2)	Ratings(-3)	Ratings(-4)	Credit Spread	Term Spread
Mean	-3.70E-04	-6.63E-05	2.61E-05	5.36E-05	9.96E-01	-5.8E-04	2.41E-03	4.04E-03	4.65E-03	3.54E-03
SE(mean)	0.000409	0.0000911	0.0000943	0.0000755	0.000784	0.00114	0.00107	0.000941	0.00114	0.00183
P-value	0.368	0.469	0.783	0.483	0.000	0.614	0.028	0.0002	0.0001	0.057
% significant	0.337	0.159	0.135	0.0357	1	0	0	0	0.347	0.313
# of positive and significant	25	3	3	1	101	0	0	0	25	25
# of negative and significant	9	7	4	0	0	0	0	0	10	6
Total	101	63	52	28	101	63	52	28	101	99

Panel C. Fitch Full Sample Results										
Equation 1	CDS(-1)	CDS(-2)	CDS(-3)	CDS(-4)	Ratings(-1)	Ratings(-2)	Ratings(-3)	Ratings(-4)	Credit Spread	Term Spread
Mean	1.084	-0.105	-0.0372	0.0135	2.285	-2.417	3.851	-8.861	-1.063	0.872
SE(mean)	0.025	0.037	0.016	0.026	1.502	5.075	3.783	5.748	0.557	0.918
P-value	0.000	0.007	0.025	0.615	0.132	0.636	0.314	0.140	0.060	0.345
% significant	1	0.778	0.622	0.579	0.225	0.185	0.067	0.263	0.213	0.238
# of positive and significant	80	14	9	5	14	5	1	3	3	4
# of negative and significant	0	28	19	6	4	5	2	2	14	15
Total	80	54	45	19	80	54	45	19	80	80
Equation 2	CDS(-1)	CDS(-2)	CDS(-3)	CDS(-4)	Ratings(-1)	Ratings(-2)	Ratings(-3)	Ratings(-4)	Credit Spread	Term Spread
Mean	8.111E-05	-6.775E-05	4.679E-05	-0.00009	0.99096	0.00385	0.00397	0.00687	0.004873	0.00187
SE(mean)	0.000176	0.000373	0.000179	9.55E-05	3.27E-03	0.00383	0.00151	0.00160	0.00258	0.00202
P-value	0.646	0.856	0.795	0.347	0.000	0.319	0.0118	0.0004	0.0622	0.359
% significant	0.263	0.148	0.156	0.105	1	0.0370	0	0	0.278	0.291
# of positive and significant	13	5	2	1	80	2	0	0	17	18
# of negative and significant	8	3	5	1	0	0	0	0	5	5
Total	80	54	45	19	80	54	45	19	79	79

Table 6. Moody's VAR Variance Decomposition

This table reports output for variance decomposition of Moody's VAR estimates. The first column lists the forecast period error being analyzed followed by the statistics calculated. Mean values are calculated by taking the arithmetic average of each estimate for that specific period. Standard errors are defined as the mean value divided by the square root of total observations. P-values are then calculated using the Student's t-distribution. The second column reports statistics on CDS variance, the third provides the percentage of CDS variance explained by CDS spreads and the fourth reports the percentage of CDS variance explained by credit ratings. The fifth column reports credit rating variance, columns six and seven report the percent of credit rating variance explained by CDS spreads and credit ratings respectively. The total number of estimated equations is 48.

1 period avgs.	CDS variance	CDS contribution	CR contribution	CR variance	CDS contribution	CR contribution
Mean	18.207	100.000	0.000	0.046	0.163	99.837
SE(mean)	4.463	0.000	0.000	0.006	0.101	0.101
p-value	0.000	0.000	0.000	0.000	0.115	0.000
2 period avgs.						
Mean	25.466	99.947	0.053	0.064	0.431	99.569
SE(mean)	6.090	0.027	0.027	0.009	0.149	0.149
p-value	0.000	0.000	0.057	0.000	0.006	0.000
3 period avgs.						
Mean	31.292	99.919	0.081	0.078	0.923	99.077
SE(mean)	7.362	0.034	0.034	0.010	0.282	0.282
p-value	0.000	0.000	0.022	0.000	0.002	0.000
4 period avgs.						
Mean	36.123	99.887	0.113	0.090	1.562	98.438
SE(mean)	8.408	0.050	0.050	0.012	0.475	0.475
p-value	0.000	0.000	0.028	0.000	0.002	0.000
5 period avgs.						
Mean	40.231	99.859	0.141	0.100	2.297	97.703
SE(mean)	9.288	0.060	0.060	0.013	0.697	0.697
p-value	0.000	0.000	0.024	0.000	0.002	0.000
6 period avgs.						
Mean	43.893	99.833	0.167	0.110	3.086	96.914
SE(mean)	10.080	0.071	0.071	0.015	0.934	0.934
p-value	0.000	0.000	0.022	0.000	0.002	0.000

Table 6. Moody's VAR Variance Decomposition (Continued)

7 period avgs.						
Mean	47.273	99.807	0.193	0.118	3.898	96.102
SE(mean)	10.828	0.081	0.081	0.016	1.174	1.174
p-value	0.000	0.000	0.021	0.000	0.002	0.000
8 period avgs.						
Mean	50.407	99.780	0.220	0.126	4.712	95.288
SE(mean)	11.535	0.092	0.092	0.017	1.410	1.410
p-value	0.000	0.000	0.021	0.000	0.002	0.000
9 period avgs.						
Mean	53.327	99.750	0.250	0.134	5.512	94.488
SE(mean)	12.197	0.104	0.104	0.018	1.637	1.637
p-value	0.000	0.000	0.020	0.000	0.001	0.000
10 period avgs.						
Mean	56.055	99.718	0.282	0.141	6.289	93.711
SE(mean)	12.820	0.117	0.117	0.019	1.851	1.851
p-value	0.000	0.000	0.020	0.000	0.001	0.000

Table 7. S&P VAR Variance Decomposition

This table reports output for variance decomposition of S&P VAR estimates. The first column lists the forecast period error being analyzed followed by the statistics calculated. Mean values are calculated by taking the arithmetic average of each estimate for that specific period. Standard errors are defined as the mean value divided by the square root of total observations. P-values are then calculated using the Student's t-distribution. The second column reports statistics on CDS variance, the third provides the percentage of CDS variance explained by CDS spreads and the fourth reports the percentage of CDS variance explained by credit ratings. The fifth column reports credit rating variance, columns six and seven report the percent of credit rating variance explained by CDS spreads and credit ratings respectively. The total number of estimated equations is 116.

1 period avgs.	CDS variance	CDS contribution	CR contribution	CR variance	CDS contribution	CR contribution
Mean	16.341	100.000	0.000	0.068	0.219	99.781
SE(mean)	3.657	0.000	0.000	0.008	0.085	0.085
p-value	0.000	0.000	0.000	0.000	0.011	0.000
2 period avgs.						
Mean	25.201	99.809	0.191	0.096	0.711	99.289
SE(mean)	6.040	0.085	0.085	0.011	0.200	0.200
p-value	0.000	0.000	0.026	0.000	0.001	0.000
3 period avgs.						
Mean	32.402	99.705	0.295	0.118	1.180	98.820
SE(mean)	8.028	0.136	0.136	0.014	0.301	0.301
p-value	0.000	0.000	0.032	0.000	0.000	0.000
4 period avgs.						
Mean	38.570	99.629	0.371	0.135	1.683	98.317
SE(mean)	9.705	0.171	0.171	0.016	0.407	0.407
p-value	0.000	0.000	0.032	0.000	0.000	0.000
5 period avgs.						
Mean	43.894	99.566	0.434	0.151	2.225	97.775
SE(mean)	11.126	0.198	0.198	0.018	0.519	0.519
p-value	0.000	0.000	0.031	0.000	0.000	0.000
6 period avgs.						
Mean	48.626	99.514	0.486	0.166	2.790	97.210
SE(mean)	12.354	0.219	0.219	0.020	0.632	0.632
p-value	0.000	0.000	0.029	0.000	0.000	0.000

Table 7. S&P VAR Variance Decomposition (Continued)

7 period avgs.						
Mean	52.905	99.466	0.534	0.179	3.368	96.632
SE(mean)	13.433	0.237	0.237	0.021	0.743	0.743
p-value	0.000	0.000	0.026	0.000	0.000	0.000
8 period avgs.						
Mean	56.794	99.419	0.581	0.191	3.951	96.049
SE(mean)	14.392	0.253	0.253	0.023	0.851	0.851
p-value	0.000	0.000	0.023	0.000	0.000	0.000
9 period avgs.						
Mean	60.352	99.373	0.627	0.202	4.534	95.466
SE(mean)	15.250	0.267	0.267	0.024	0.956	0.956
p-value	0.000	0.000	0.021	0.000	0.000	0.000
10 period avgs.						
Mean	63.631	99.325	0.675	0.213	5.111	94.889
SE(mean)	16.024	0.282	0.282	0.025	1.057	1.057
p-value	0.000	0.000	0.018	0.000	0.000	0.000

Table 8. Fitch VAR Variance Decomposition

This table reports output for variance decomposition of Fitch VAR estimates. The first column lists the forecast period error being analyzed followed by the statistics calculated. Mean values are calculated by taking the arithmetic average of each estimate for that specific period. Standard errors are defined as the mean value divided by the square root of total observations. P-values are then calculated using the Student's t-distribution. The second column reports statistics on CDS variance, the third provides the percentage of CDS variance explained by CDS spreads and the fourth reports the percentage of CDS variance explained by credit ratings. The fifth column reports credit rating variance, columns six and seven report the percent of credit rating variance explained by CDS spreads and credit ratings respectively. The total number of estimated equations is 80.

1 period avgs.	CDS variance	CDS contribution	CR contribution	CR variance	CDS contribution	CR contribution
Mean	16.124	100.000	0.000	0.078	0.731	99.269
SE(mean)	3.590	0.000	0.000	0.012	0.344	0.344
p-value	0.000	0.000	0.000	0.000	0.037	0.000
2 period avgs.						
Mean	23.263	99.807	0.193	0.108	0.936	99.064
SE(mean)	5.065	0.086	0.086	0.017	0.393	0.393
p-value	0.000	0.000	0.027	0.000	0.020	0.000
3 period avgs.						
Mean	28.906	99.733	0.267	0.132	1.409	98.591
SE(mean)	6.237	0.110	0.110	0.020	0.477	0.477
p-value	0.000	0.000	0.018	0.000	0.004	0.000
4 period avgs.						
Mean	33.643	99.645	0.355	0.151	2.027	97.973
SE(mean)	7.218	0.128	0.128	0.023	0.609	0.609
p-value	0.000	0.000	0.007	0.000	0.001	0.000
5 period avgs.						
Mean	37.775	99.593	0.407	0.168	2.721	97.279
SE(mean)	8.080	0.141	0.141	0.026	0.777	0.777
p-value	0.000	0.000	0.005	0.000	0.001	0.000
6 period avgs.						
Mean	41.536	99.559	0.441	0.184	3.441	96.559
SE(mean)	8.874	0.148	0.148	0.028	0.958	0.958
p-value	0.000	0.000	0.004	0.000	0.001	0.000

Table 8. Fitch VAR Variance Decomposition

7 period avgs.						
Mean	45.046	99.536	0.464	0.198	4.165	95.835
SE(mean)	9.628	0.153	0.153	0.030	1.139	1.139
p-value	0.000	0.000	0.003	0.000	0.000	0.000
8 period avgs.						
Mean	48.331	99.517	0.483	0.211	4.875	95.125
SE(mean)	10.349	0.157	0.157	0.032	1.314	1.314
p-value	0.000	0.000	0.003	0.000	0.000	0.000
9 period avgs.						
Mean	51.427	99.501	0.499	0.223	5.559	94.441
SE(mean)	11.043	0.160	0.160	0.034	1.479	1.479
p-value	0.000	0.000	0.003	0.000	0.000	0.000
10 period avgs.						
Mean	54.373	99.486	0.514	0.235	6.212	93.788
SE(mean)	11.715	0.163	0.163	0.036	1.635	1.635
p-value	0.000	0.000	0.002	0.000	0.000	0.000

Table 9. VEC Estimation Results

This table provides results from VEC estimation including Ratings and CDS spreads as endogenous variables. Panel A reports results from Moody's, Panel B reports S&P results and Panel C provides Fitch results. Each regression includes a constant and two exogenous variables; credit spread and term spread. Equation 1 specifies the first difference of CDS spreads as the dependent variable, equation 2 specifies first differenced credit ratings as the dependent variable. For each parameter mean, standard error, p-value, percentage significant, percentage positive and significant and percentage negative and significant are reported. Mean values are calculated by taking the arithmetic average of point estimates. Standard errors are calculated by dividing the standard deviation of the parameter by the square root of the number of estimated coefficients. P-values are calculated using the Student's t-distribution.

Panel A. Moody's Full Sample Results

Equation 1	Cointegrating Eq.	CDS(-1)	CDS(-2)	CDS(-3)	CDS(-4)	RATINGS (-1)	RATINGS (-2)	RATINGS (-3)	RATINGS (-4)	Credit Spread	Term Spread	Constant
Mean	-0.0102	0.229	0.0329	0.000833	0.00497	-2.140	9.742	-3.617	2.716	5.975	-1.426	-1.049
SE(mean)	0.00149	0.0344	0.0256	0.0281	0.0311	4.747	4.229	7.213	2.950	1.778	0.413	1.395
P-value	1.37E-08	2.46E-08	0.208	0.977	0.875	0.654	0.027	0.621	0.367	0.002	0.001	0.456
% significant	0.813	0.875	0.735	0.609	0.636	0.250	0.294	0.217	0.091	0.396	0.354	0.438
# of positive and significant	1	36	17	7	7	7	8	2	2	18	1	3
# of negative and significant	38	6	8	7	7	5	2	3	0	1	16	18
Total	48	48	34	23	22	48	34	23	22	48	48	48
Equation 2	**Cointegrating Eq.**	**CDS(-1)**	**CDS(-2)**	**CDS(-3)**	**CDS(-4)**	**RATINGS (-1)**	**RATINGS (-2)**	**RATINGS (-3)**	**RATINGS (-4)**	**Credit Spread**	**Term Spread**	**Constant**
Mean	-4.37E-06	0.00016	6.21E-05	2.84E-05	0.000273	-0.0113	-0.00973	-0.01611	-0.00771	-0.0289	0.00459	0.00974
SE(mean)	2.19E-05	0.000150	0.000122	9.13E-05	0.000206	0.00399	0.00358	0.00730	0.003262	0.0248	0.00374	0.00582
P-value	0.842	0.281	0.614	0.758	0.199	0.007	0.010	0.038	0.027	0.249	0.226	0.101
% significant	0.354	0.229	0.059	0.261	0.182	0.021	0.029	0.043	0	0.125	0.083	0.104
# of positive and significant	12	7	0	2	3	0	0	0	0	1	3	4
# of negative and significant	5	4	2	4	1	1	1	1	0	5	1	1
Total	48	48	34	23	22	48	34	23	22	48	48	48

Table 9 - VEC Estimation Results (Continued)

Panel B. S&P Full Sample Results

Equation 1	Cointegrating Eq.	CDS(-1)	CDS(-2)	CDS(-3)	CDS(-4)	RATINGS (-1)	RATINGS (-2)	RATINGS (-3)	RATINGS (-4)	Credit Spread	Term Spread	Constant
Mean	-0.00916	0.221	0.0402	0.0237	-0.0160	11.289	8.043	44.026	9.619	7.673	-1.838	0.0519
SE(mean)	0.00115	0.0208	0.0128	0.0100	0.016	5.573	5.596	36.803	11.801	1.747	0.414	1.645
P-value	3.98E-12	1.20E-17	0.002421	0.021	0.331	0.046	0.155	0.236	0.421	3E-05	2.51E-05	0.975
% significant	0.82417582	0.9011	0.701299	0.40625	0.6875	0.26374	0.24675	0.21875	0.25	0.40659	0.40659	0.41758
# of positive and significant	6	73	39	18	10	22	10	11	4	36	1	3
# of negative and significant	69	9	15	8	12	2	9	3	4	1	36	35
Total	91	91	77	64	32	91	77	64	32	91	91	91

Equation 2	Cointegrating Eq.	CDS(-1)	CDS(-2)	CDS(-3)	CDS(-4)	RATINGS (-1)	RATINGS (-2)	RATINGS (-3)	RATINGS (-4)	Credit Spread	Term Spread	Constant
Mean	1.74E-05	3.06E-06	-6.40E-06	5.64E-06	-0.000156	-0.00527	-0.00486	0.00398	-0.00885	-0.00174	0.000795	0.00217
SE(mean)	6.03E-06	6.59E-05	4.56E-05	8.52E-05	0.000133	0.00136	0.00178	0.00660	0.003313	0.00254	0.000582	0.00378
P-value	0.00491	0.963	0.889	0.947	0.247	0.000203	0.00791	0.548	0.0118	0.496	0.176	0.567
% significant	0.440	0.242	0.169	0.234	0.219	0.011	0.013	0.063	0.063	0.088	0.077	0.132
# of positive and significant	29	15	7	6	3	1	1	2	0	3	5	6
# of negative and significant	11	7	6	9	4	0	0	2	2	5	2	6
Total	91	91	77	64	32	91	77	64	32	91	91	91

Panel C. Fitch Full Sample Results

Equation 1	Cointegrating Eq.	CDS(-1)	CDS(-2)	CDS(-3)	CDS(-4)	RATINGS (-1)	RATINGS (-2)	RATINGS (-3)	RATINGS (-4)	Credit Spread	Term Spread	Constant
Mean	-0.00800	0.213	0.0534	0.00118	-0.00756	-6.675	2.871	0.651	-1.738	5.336	-1.300	-0.304
SE(mean)	0.00133	0.0265	0.0180	0.0126	0.0148	7.496	1.309	1.208	3.857	2.221	0.509	2.288
P-value	8.8716E-08	2E-11	0.004321	0.925406	0.614104	0.37642	0.0323	0.59223	0.6556	0.01905	0.01299	0.89459
% significant	0.866	0.881	0.793	0.442	0.552	0.194	0.172	0.096	0.172	0.284	0.269	0.403
# of positive and significant	5	53	35	13	8	12	7	1	2	19	1	2
# of negative and significant	53	6	11	10	8	1	3	4	3	0	17	25
Total	67	67	58	52	29	67	58	52	29	67	67	67

Equation 2	Cointegrating Eq.	CDS(-1)	CDS(-2)	CDS(-3)	CDS(-4)	RATINGS (-1)	RATINGS (-2)	RATINGS (-3)	RATINGS (-4)	Credit Spread	Term Spread	Constant
Mean	2.79E-05	5.20E-05	0.000172	-0.000144	4.10E-05	-0.00536	-0.00302	-0.00649	-0.000779	-0.00241	0.000280	0.0109
SE(mean)	2.27E-05	7.48E-05	7.61E-05	4.69E-05	5.43E-05	0.00140	0.00201	0.00230	0.00312	0.00246	0.000595	0.00599
P-value	0.22442247	0.48937	0.028057	0.003402	0.45634	0.0003	0.13766	0.00689	0.804769	0.32935	0.6394	0.07376
% significant	0.43283582	0.13433	0.12069	0.173077	0.241379	0.02985	0.01724	0.01923	0.034483	0.07463	0.04478	0.1194
# of positive and significant	25	6	5	2	5	0	1	0	1	0	3	8
# of negative and significant	4	3	2	7	2	2	0	1	0	5	0	0
Total	67	67	58	52	29	67	58	52	29	67	67	67

Table 10. Moody's VEC Variance Decomposition

This table reports the results from Moody's VEC variance decomposition. The first column lists the forecast period error being analyzed followed by the statistics calculated. Mean values are calculated by taking the arithmetic average of each estimate for that specific period. Standard errors are defined as the mean value divided by the square root of total observations. P-values are then calculated using the Student's t-distribution. The second column reports statistics on CDS variance, the third provides the percentage of CDS variance explained by CDS spreads and the fourth reports the percentage of CDS variance explained by credit ratings. The fifth column reports credit rating variance, columns six and seven report the percent of credit rating variance explained by CDS spreads and credit ratings respectively. 48 equations are estimated in total.

1 period avgs.	CDS variance	CDS contribution	CR contribution	CR variance	CDS contribution	CR contribution
Mean	12.815	100.000	0.000	0.060	0.837	99.163
SE(mean)	1.981	0.000	0.000	0.005	0.342	0.342
p-value	0.00	0.00	0.00	0.00	0.02	0.00
2 period avgs.						
Mean	22.763	99.737	0.263	0.083	1.218	98.782
SE(mean)	3.928	0.123	0.123	0.007	0.459	0.459
p-value	0.00	0.00	0.04	0.00	0.01	0.00
3 period avgs.						
Mean	29.935	99.542	0.458	0.101	1.455	98.545
SE(mean)	5.332	0.189	0.189	0.009	0.572	0.572
p-value	0.00	0.00	0.02	0.00	0.01	0.00
4 period avgs.						
Mean	36.160	99.290	0.710	0.116	1.755	98.245
SE(mean)	6.604	0.291	0.291	0.010	0.770	0.770
p-value	0.00	0.00	0.02	0.00	0.03	0.00
5 period avgs.						
Mean	41.682	99.001	0.999	0.129	1.991	98.009
SE(mean)	7.762	0.397	0.397	0.011	0.934	0.934
p-value	0.00	0.00	0.02	0.00	0.04	0.00
6 period avgs.						
Mean	46.677	98.810	1.190	0.140	2.173	97.827
SE(mean)	8.819	0.467	0.467	0.012	1.071	1.071
p-value	0.00	0.00	0.01	0.00	0.05	0.00
7 period avgs.						
Mean	51.149	98.676	1.324	0.151	2.319	97.681
SE(mean)	9.778	0.514	0.514	0.013	1.176	1.176
p-value	0.00	0.00	0.01	0.00	0.05	0.00

Table 10. Moody's VEC Variance Decomposition (Continued)

8 period avgs.						
Mean	55.174	98.574	1.426	0.160	2.447	97.553
SE(mean)	10.656	0.544	0.544	0.014	1.262	1.262
p-value	0.00	0.00	0.01	0.00	0.06	0.00
9 period avgs.						
Mean	58.885	98.479	1.521	0.170	2.563	97.437
SE(mean)	11.467	0.567	0.567	0.014	1.333	1.333
p-value	0.00	0.00	0.01	0.00	0.06	0.00
10 period avgs.						
Mean	62.347	98.388	1.612	0.178	2.671	97.329
SE(mean)	12.225	0.584	0.584	0.015	1.392	1.392
p-value	0.00	0.00	0.01	0.00	0.06	0.00

Table 11. S&P VEC Variance Decomposition

This table reports the results from S&P VEC variance decomposition. The first column lists the forecast period error being analyzed followed by the statistics calculated. Mean values are calculated by taking the arithmetic average of each estimate for that specific period. Standard errors are defined as the mean value divided by the square root of total observations. P-values are then calculated using the Student's t-distribution. The second column reports statistics on CDS variance, the third provides the percentage of CDS variance explained by CDS spreads and the fourth reports the percentage of CDS variance explained by credit ratings. The fifth column reports credit rating variance, columns six and seven report the percent of credit rating variance explained by CDS spreads and credit ratings respectively. 91 equations are estimated in total.

1 period avgs.	CDS Variance	CDS Contribution	CR Contribution	CR Variance	CDS Contribution	CR Contribution
Mean	15.987	100	0	0.059	0.615	99.385
SE(mean)	2.603	0	0	0.004	0.199	0.199
p-value	0	0		0	0	0
2 period avgs.						
Mean	24.873	99.893	0.107	0.084	0.827	99.173
SE(mean)	3.935	0.023	0.023	0.006	0.221	0.221
p-value	0	0	0	0	0	0
3 period avgs.						
Mean	32.104	99.725	0.275	0.102	1.065	98.935
SE(mean)	5.072	0.071	0.071	0.008	0.25	0.25
p-value	0	0	0	0	0	0
4 period avgs.						
Mean	38.654	99.383	0.617	0.118	1.263	98.737
SE(mean)	6.132	0.163	0.163	0.009	0.266	0.266
p-value	0	0	0	0	0	0
5 period avgs.						
Mean	44.681	99.024	0.976	0.132	1.458	98.542
SE(mean)	7.16	0.286	0.286	0.01	0.295	0.295
p-value	0	0	0	0	0	0
6 period avgs.						
Mean	50.156	98.786	1.214	0.144	1.613	98.387
SE(mean)	8.145	0.346	0.346	0.011	0.32	0.32
p-value	0	0	0	0	0	0

Table 11. S&P VEC Variance Decomposition (Continued)

7 period avgs.						
Mean	55.316	98.553	1.447	0.156	1.739	98.261
SE(mean)	9.137	0.443	0.443	0.012	0.338	0.338
p-value	0.00	0.00	0.00	0.00	0.00	0.00
8 period avgs.						
Mean	60.270	98.325	1.675	0.167	1.861	98.139
SE(mean)	10.158	0.553	0.553	0.013	0.357	0.357
p-value	0.00	0.00	0.00	0.00	0.00	0.00
9 period avgs.						
Mean	65.048	98.133	1.867	0.177	1.971	98.029
SE(mean)	11.217	0.644	0.644	0.013	0.376	0.376
p-value	0.00	0.00	0.00	0.00	0.00	0.00
10 period avgs.						
Mean	69.667	97.956	2.044	0.186	2.067	97.933
SE(mean)	12.337	0.723	0.723	0.014	0.392	0.392
p-value	0.00	0.00	0.01	0.00	0.00	0.00

Table 12. Fitch VEC Variance Decomposition

This table reports the results from Fitch VEC variance decomposition. The first column lists the forecast period error being analyzed followed by the statistics calculated. Mean values are calculated by taking the arithmetic average of each estimate for that specific period. Standard errors are defined as the mean value divided by the square root of total observations. P-values are then calculated using the Student's t-distribution. The second column reports statistics on CDS variance, the third provides the percentage of CDS variance explained by CDS spreads and the fourth reports the percentage of CDS variance explained by credit ratings. The fifth column reports credit rating variance, columns six and seven report the percent of credit rating variance explained by CDS spreads and credit ratings respectively. 67 equations in total are estimated.

1 period avgs.	CDS Variance	CDS Contribution	CR Contribution	CR Variance	CDS Contribution	CR Contribution
Mean	14.460	100.000	0.000	0.074	0.579	99.421
SE(mean)	2.815	0.000	0.000	0.010	0.225	0.225
p-value	0	0		0	0.01	0
2 period avgs.						
Mean	22.910	99.179	0.821	0.102	0.758	99.242
SE(mean)	4.408	0.650	0.650	0.014	0.256	0.256
p-value	0	0	0.21	0	0.004	0
3 period avgs.						
Mean	29.976	98.964	1.036	0.125	0.989	99.011
SE(mean)	5.768	0.750	0.750	0.017	0.352	0.352
p-value	0	0	0.17	0	0.007	0
4 period avgs.						
Mean	35.722	98.854	1.146	0.143	1.114	98.886
SE(mean)	6.846	0.797	0.797	0.019	0.398	0.398
p-value	0	0	0.16	0	0.007	0
5 period avgs.						
Mean	40.786	98.724	1.276	0.159	1.201	98.799
SE(mean)	7.799	0.846	0.846	0.021	0.425	0.425
p-value	0	0	0.14	0	0.006	0
6 period avgs.						
Mean	45.285	98.659	1.341	0.174	1.284	98.716
SE(mean)	8.647	0.869	0.869	0.023	0.446	0.446
p-value	0	0	0.13	0	0.005	0

Table 12. Fitch VEC Variance Decomposition (Continued)

7 period avgs.						
Mean	49.358	98.615	1.385	0.187	1.370	98.630
SE(mean)	9.416	0.885	0.885	0.025	0.461	0.461
p-value	0	0	0.12	0	0.004	0
8 period avgs.						
Mean	53.050	98.581	1.419	0.199	1.462	98.538
SE(mean)	10.116	0.894	0.894	0.026	0.473	0.473
p-value	0	0	0.12	0	0.003	0
9 period avgs.						
Mean	56.455	98.554	1.446	0.210	1.565	98.435
SE(mean)	10.763	0.899	0.899	0.028	0.487	0.487
p-value	0	0	0.11	0	0.002	0
10 period avgs.						
Mean	59.617	98.528	1.472	0.221	1.679	98.321
SE(mean)	11.366	0.905	0.905	0.029	0.504	0.504
p-value	0	0	0.11	0	0.001	0